LOOKING UP THE SKY: UNIDENTIFIED AERIAL PHENOMENA AND MACROECONOMIC ATTENTION[1]

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Abstract: Attention to information plays a key role in recent macroeconomic analysis, yet measuring it is a challenging endeavor, most notably in terms of covering varying geographical levels and time frequencies. We propose a novel, unconventional measure of public attention, which addresses these limitations, based on individuals' reports of Unidentified Aerial Phenomena (UAP). We document a surprising link between UAP sightings and macroeconomic conditions at the U.S.-county, state, and national levels. Controlling for weather conditions, and external influences, UAP sightings are more common in wealthier regions, but within regions the pattern is counter-cyclical. Thus, variations in attention to exceptional phenomena in the skies point at more general patterns of variations in the public attention. We further support this interpretation by a quasi-experimental design that utilizes plausibly exogenous regional variations in COVID-19 restrictions and find evidence for a causal effect on public attention. We further show that the UAP sightings measure is highly correlated with conventional measures of attention that are based on expectations data. We then apply our measure in the context of monetary policy transmission. We find that it can account for sizable regional heterogeneity in the response to monetary shocks. Higher levels of attention across U.S. regions, as well as within regions over the business cycle, substantially mitigate the effect of monetary policy.

Keywords: Rational inattention, monetary policy, UAP

JEL codes: E31; C83; D84

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1. Introduction

Attention to information plays a key role in recent macroeconomic analysis.[2] Variations in attention across agents and over time can be explained by models of rational inattention, in which costly information is processed by an optimization mechanism.[3] Yet, measuring variations in public attention across geographical locations and resolutions, as well as across time frequencies, in addition to assessing its role remains a challenging task. The growing empirical literature on public attention relies primarily on measures based on expectations and perceptions in survey data. However, survey data is mainly available for professionals, while the attention of the general public differs substantially both in level and heterogeneity.[4] In addition, survey data is limited by its geographical coverage as well as available time frequency.[5] Addressing these limitations is, thus, central for studying the role of the attention channel in macroeconomic analysis. This study proposes a novel measure of public attention, based on an unconventional dataset, namely individuals' attention to the skies via the extent of reports on Unidentified Aerial Phenomena (UAP). The measure we propose is rich in its geographical heterogeneity, is consistent across locations, and is available at high time frequencies (daily level); thus, it fills the noted gaps with respect to the empirical measurement of macroeconomic attention.

Why would attention to the skies be a reasonable proxy for attention to the economy? The literature on attention does not provide a clear answer. Attention to the skies might be a unique form of attention which is uncorrelated with economic attention. Conversely, it can be negatively correlated with economic attention if both types of attention compete for the same limited resources, consistent with theories of limited attention.[6] Recent evidence from behavioral and experimental studies, however, point at a third possible alternative; namely, the option that the two types of attention may behave like complements.[7] Under this possibility, if people pay more attention to economic conditions, they may also become more aware of their surroundings (or vice versa), including the skies. This study applies several empirical strategies that strongly support the third alternative, as we elaborate below, motivating an interpretation of an attention nexus between sky viewing and economic information.

Our approach follows the recent shift in the literature to depart from survey-based methods to measuring attention. The notion that agents may form expectations based on direct observations in their daily lives has been laid out by earlier contributions.[8] Recent studies provide empirical support for this

[2] Since the seminal works by Mankiw and Reis (2002) Woodford (2003) and Sims (2003), it is acknowledged that information frictions can account for sluggish responsiveness to macroeconomic shocks and policies.
[3] Coibion et al. (2018), and Maćkowiak et al. (2023) provide a synthesis of the literature.
[4] Coibion et al. (2020), Coibion et al. (2022), D'Acunto et al. (2023).
[5] For instance, two primary U.S.-based surveys, namely the Survey of Professional Forecasters and the Michigan Survey of Consumers, are available at either monthly or quarterly frequencies, and geographically at the U.S. national or large-regional (covering four aggregate regions) levels.
[6] See, e.g., Gabaix (2019) and references therein.
[7] E.g., Miyahara et al. (2006), and Schmitt and Schlatterer (2021) report that attention to secondary tasks complements, and does not come at the expense of, the attention given to primary tasks.
[8] See, e.g., the Lucas' Islands Model (1972).

notion (Cavallo et al., 2017; D'Acunto et al., 2021), illustrating that macroeconomic attention of households is associated with everyday experience. Other studies propose a textual analysis of firms' regulatory filings as an alternative useful measure of their attention (Flynn and Sastry, 2021; Song and Stern, 2021). Additional, case-specific, studies measure the attention given to financial decisions via search queries (Mondria et al., 2010; De los Santos et a., 2012). Finally, experimental, in-lab efforts to measure attention are abundant, as noted by Maćkowiak et al. (2023). Notably, similar to the conventional, survey-based measures, these alternative measures are also constrained by their potential time and geographic coverage; in addition, their relative specificity limits their scope for measuring macroeconomic attention. Departing as well from the survey-based approach, we propose linking the extent of sky-viewing to public attention. To guide our intuition, motivated by a focus on macroeconomic attention, we consider this via the lens of the rational inattention hypothesis.

Paying attention to the skies, and reporting observations, is a costly endeavor as it exhausts resources, such as time and effort, that translate to relatively little to no income for the average observer. Conversely, paying attention to the economy requires resources as well, but bears potentially higher stakes, as it directly concerns income, and for some, economic survival. Attending income is often times a necessity, a fundamental concern even, of everyday life, while observing the sky (and more so, to the extent of reporting anomalies) is more of a luxurious action, undertaken at leisure. Standard models of rational inattention suggest that, under limited resources, agents are relatively less attentive to costly information (Maćkowiak et al., 2023). In line with these models, taken together with the above interpretations, we conjecture that if rational agents notice and report anomalies in the skies, they do so in addition to paying attention to more fundamental concerns, such as information concerning the economy. This perspective is consistent with the previously noted attention complementarities alternative considered in theories of attention, in which the scope of attention given to primary and secondary tasks is considered concurrently.

We, thus, conjecture that variations in the extent of attention to the skies may represent more general patterns of attention that are also related to economic conditions. Our main analysis aims to support this conjecture in several ways. First, we document a surprising link between the extent of reported UAP sightings and economic conditions at the U.S. county, state, and national levels. Importantly, the relationship goes in *opposite* directions in the cross-section and over time, in a way that is consistent with patterns of attention documented by the literature. Second, using a quasi-experimental design that utilizes regional variations in COVID-19 restrictions, we document a causal effect of an attention shock on the measure of UAP sightings. Third, we show that the measure of UAP sightings is highly correlated with conventional measures of rational inattention that are based on expectations data. Building on this evidence, we exploit the richness of UAP sightings data and apply it as a novel measure of attention in the context of monetary policy transmission. We find that, consistent with predictions of the literature, this attention measure accounts for sizable regional heterogeneity in the response to monetary shocks.

We consider UAPs. The latter refer to objects in the sky that reporting individuals interpret as being unidentified, previously also referred to as Unidentified Flying Objects (UFOs). The term has been recently updated by the U.S. Pentagon (U.S. Pentagon, 2021), to account for its broader perspective which includes various types of aerial phenomena, including natural phenomena. Importantly, the latter represents the vast majority of individuals' observations, as official investigations of various countries reveal. For instance, the U.S. Air Force concludes in its Project Bluebook Reference Report,[9] which officially investigated various UAPs reported by individuals across the U.S. throughout the 1950s and 1960s, that out of 12,618 investigated cases, only 701 remained unidentified (i.e., about 5% of observations). Similar conclusions were drawn by a study of UAP reports conducted by NASA in 2023,[10] as well as by official investigations held by the governments of additional countries, such as Canada, the U.K., and France, among others (see, e.g., Joyce, 2022). Based on the wide scope of the natural origins of these observations, we hypothesize that, controlling for local characteristics, weather conditions, and seasonality, the patterns and extent of these reports are deeply rooted in human and social behavior, driven by individuals' attention to the skies.

Indeed, examining the skies is a feature of everyday life, the extent of which depends on the extent of attention given to them. We therefore propose, as noted, measuring the extent of this attention via the number of individuals' reports of aerial phenomena which appear unusual. UAPs have been reported around the globe for centuries, via local established (often state-official) organizations, that have been collecting these data in high detail across long periods. Within the U.S., our focus in this study, a major such organization is NUFORC (National UFO Reporting Center). Individuals from across the U.S. report to NUFORC in case of an observation in the skies which they find unusual; this observation is then recorded in detail, including the individual's location, and time stamp. Notably, reporting to NUFORC in the case of an unidentified observable in the skies is not merely a consequence of personal preference, but is also the route that the U.S. Federal Aviation Agency (FAA) officially recommends to take.[11] NUFORC, thus, represents a central, official source of U.S. UAP reports. Our analysis focuses on the unique NUFORC dataset. The current effort marks, to our best knowledge, a first attempt to study these data and exploit their rich features in the context of their economic roots. Exploiting the location and time stamp of observations, we construct a daily-level panel across U.S. counties for the post-2000 period, which we then aggregate to different levels across the two dimensions, namely time and geography, depending on the analysis conducted.

To establish the link between attention and the extent of UAP reports, we begin by testing the extent to which the number of UAP sightings is associated with changes in key macroeconomic factors, primarily at the U.S. county (though also at the state and national) level, controlling for local factors

[9] The report is available publicly at the U.S. National Security Agency website: https://www.nsa.gov/
[10] Details are available at NASA's webpage at: https://science.nasa.gov/uap
[11] See the FAA's Air Traffic Control Procedures, Chapter 9, Section 8.

and weather conditions, as well as for the extent of Google searches of this phenomenon (accounting for media and other external influences), in addition to a host of further controls, ranging from the existence of military installments and extent of mental health to other state-by-year differences (such as, e.g., cultural or political differences). Interestingly, although attention to the skies is focused on a unique phenomenon, we find that variations in reported sightings are robustly correlated with macroeconomic conditions both across regions and over time. Strikingly, we document that the cross-sectional and time correlations go in *opposite* ways, in robust and precise magnitudes. While reports on UAP sightings are more common in wealthier U.S. counties and states, the pattern over time, within regions, is counter-cyclical. Such patterns suggest that UAP sightings may not just represent some exotic forms of beliefs, or be an outcome of mental impacts. Rather, the patterns we document are consistent with evidence on varying attention, based on economic expectations. Specifically, the literature finds that attention tends to increase during recessions (Coibion and Gordonichenko, 2015; Goldstein, 2023), and households from higher socioeconomic backgrounds have macroeconomic expectations with lower errors and biases (Bruine de Bruin et al., 2010; Angelico and Di Giacomo, 2020; Das, Kuhnen, and Nagel, 2020). Thus, the extent of UAP sightings seems to capture broader patterns of public attention, with an important dimension of variation at the regional level.

In an attempt to go beyond the conventional conditional-correlations framework, and in addition present an application of the unique daily frequency of our proposed measure, we further support the attention interpretation by exploiting the daily variation in UAP sightings around the COVID-19 lockdowns. We use difference-in-differences and event study designs based on plausibly exogenous time differentials in COVID restriction orders across U.S. counties. Specifically, we adopt a restrictions-index, retrieved from the U.S. Center for Disease Control and Prevention (CDC), which measures the extent of lockdown restrictions at the daily level across counties. The extent of these restrictions ranges between having no orders in place and a stay-at-home order (with varying degrees of restrictions in-between), having ample plausibly exogenous, cross-sectional and time, variation. We examine the daily impact of this index on the extent of UAP sightings over the 2019-2020 period, where 2019 acts as a baseline year. We document a causal link between the extent of lockdowns and the number of UAP sightings. Notably, lockdown-induced sightings are also robust to variations in UAP internet searches during this special period. Importantly, UAP sightings do not respond abruptly to lockdowns. Instead, the increase in sightings evolves very gradually during the two weeks since the beginning of a lockdown. This evidence is in line with evolving public attention which is captured by the UAP sightings indicator.

Following the above results, we directly compare our novel proxy for public attention to conventional measures of inattention that are based on expectations data. Specifically, we apply and extend the measure of Coibion and Gorodnichenko (2015), which is based on the relation between forecast errors and forecast revisions at the aggregate level, and the measure of Goldstein (2023), which is based on the persistence of deviations of individual forecasts from the mean forecast. Despite a small sample period, we find a significant negative correlation over time between the two expectations-based measures and the UAP sightings measure; thus, supporting the interpretation of our novel measure as a proxy for public attention. We further decompose the inattention measure of Goldstein (2023) by different macroeconomic variables and find that the documented correlation is mainly driven by the GDP variables. Thus, our measure can be interpreted as capturing public attention to the state of the economy in a broader sense.

As highlighted above, the main advantage of our proposed measure of attention, relative to conventional measures is in the richer dimensions of variations, primarily the geographical variations. In our final analysis, we exploit this advantage and apply our proposed measure of public attention to examine a new type of heterogeneity in the effect of monetary policy. Following the literature on monetary non-neutrality, monetary policy should be less effective when agents are more attentive. Thus, if our measure can track levels of attention across different U.S. regions, it will be able to explain different responses across regions to a monetary shock induced by a Federal Reserve decision at the national level. We estimate the impulse response of U.S. states and counties to monetary shocks derived by high-frequency identification around the U.S. Federal Open Market Committee (FOMC) meetings. Our key finding is that the regional response to monetary policy is substantially mitigated if the local level of attention, measured by our proxy, is relatively high. This observation is highly robust to a host of tests, including an IV approach that instruments UAP sightings via plausibly exogenous income shocks manifested by changes in the oil price interacted with geologically-based natural resource reserves. Quantitatively, a one standard deviation (annual) increase in the number of UAP sightings at the county level suggests that the average annual impact of a 25 basis points hike in the Federal Funds Rate on local GDP and employment decreases by 2.5 percentage points. Hence, our measure of attention can account for a sizable variation in the effect of monetary policy across regions as well as within regions over the business cycle.

The remainder of the paper is organized as follows. Section 2 places the contribution of the current effort within the related literature. Section 3 describes in detail the dataset on UAP sightings and other sources of data employed in the analysis. Section 4 reports results on the link between UAP sightings and economic conditions. Section 5 presents the COVID-19 exercise. Section 6 undertakes comparisons between our measure and previous ones. Section 7 applies the UAP sightings data to the analysis of monetary policy transmission. Section 8 provides concluding remarks.

2. Related literature

This paper is related to several strands of literature. First, a growing literature highlights the macroeconomic role of information frictions and inattention. Seminal works by Sims (2003) and

Maćkowiak and Wiederholt (2009, 2015) have introduced the idea of rational inattention, where limited attention to economic conditions is micro-founded, based on the idea that people optimally choose how much costly information should be acquired. Other studies (e.g., Mankiw and Reis, 2002; Woodford, 2003) have formalized the notion of imperfect information in different ways. More recently, several studies have proposed that inattention is driven by both imperfect information and behavioral tendencies (e.g., Angeletos et al., 2020; Bordalo et al, 2020). Inattention to information has profound implications for macroeconomic fluctuations since it can rationalize the gradual response to shocks by economic agents (see reviews by Mankiw and Reis, 2010, Angeletos and Lian, 2016; Coibion et al., 2018; and Maćkowiak et al., 2023). We contribute to this literature by showing that public attention, measured by our proposed indicator, both corresponds to macroeconomic fluctuations and accounts for regional and time variations in the response to monetary shocks.

Second, following the theoretical emphasis on inattention, the literature proposes and analyzes empirical measures of attention, focusing most notably on survey data, mostly from professional forecasters. While parameters of inattention can be estimated indirectly, based on an underlying macroeconomic model, survey data on macroeconomic expectations can provide more direct estimates. The recent literature has provided such estimates, using expectations data both at the mean level (Coibion and Gorodnichenko, 2012, 2015) and at the individual level (Andrade and LeBihan, 2013; Goldstein, 2023; Kohlhas and Walther, 2021). In particular, it was found that inattention to information has largely increased following the Great Moderation and it varies with the business cycle, where recessions induce a growing attention. The COVID-19 pandemic, examined in our analysis, is a prominent example for a crisis that shifted public attention (Binder, 2020; Coibion et al., 2021; Fetzer et al., 2021). A central limitation in using expectations to measure attention is data availability. In addition, recent evidence suggests that attention to macroeconomic conditions by households and firms is much lower relative to professional forecasters (Coibion et al., 2020), but survey data on these agents is still in scarce. Consequently, recent studies depart from the survey-based approach, and attempt to measure attention using alternative methods, including textual analysis (Song and Stern, 2021; Flynn and Sastry, 2021), grocery prices (Cavallo et al., 2017; D'Acunto et al., 2021), and case-specific Google searches (Mondria et al., 2010; De los Santos et a., 2012), yet they present measures that are also constrained by their coverage. Following the latter approach, this paper proposes a novel measure of public attention, building on sky-viewing experience reflected in UAP sightings. Unlike the conventional measures, our proposed measure provides rich variations in both time and geographic domains. We illustrate, however, that its patterns across time, as well as its interaction with economic indicators, are consistent with those exhibited by the conventional measures.

A third related literature studies the heterogenous effects of monetary policy along various dimensions, such as volatility (Varva, 2014), marginal propensity to consume (Auclert, 2019), durable consumption (Sterk and Tenreyro, 2018; Mckay and Wieland, 2021), consumption risk (Acharya et al., 2020; Bilbiie, 2021), default risk (Ottonello and Winberry, 2021), or natural resource abundance (Raveh, 2020). One of the main channels for heterogenous effects is due to attention to information. Variations in attention over time can account for weaker response to monetary policy during recessions (Tenreyro and Thwaites, 2016). Cross-sectional variation in firms' attention can account for heterogeneity in their response to monetary shocks (Song and Stern, 2021). Here we apply our proposed measure of public attention to document a new type of regional heterogeneous response to monetary policy in the U.S., finding that, consistent with the literature, it accounts for much of the cross-sectional and time variation in the effect of monetary policy across regions.

Fourth, this study is also a pioneering effort to shed light on the widely ignored phenomenon of UAP sightings. UAPs have been reported around the globe for centuries, but due to various reasons, most notably the fear of potential ridicule, this topic received little to no attention within the academic community, despite representing a widely occurring phenomenon (Wendt and Duvall, 2008). This disregard may reflect the largely speculative scientific attitude to this phenomenon (Eghigian, 2017). The recent years, however, have brought a drastic change to this topic, to the point that it is now gaining acceptance and debated openly by high rank officials, army personnel, mainstream media, and the public, across many nations.[12] Consequent public debates call for investigations at all levels. Nonetheless, to our best knowledge, rigorous examinations from economic perspectives have yet to appear.[13] This paper is the first to document a robust association between economic factors and patterns of UAP sightings, giving rise to the attention mechanism and its macroeconomic implications.

Fifth, also related is the literature on the association between business cycles and mental health. Guerra and Eboreime (2021) and Frasquilho et al. (2015) provide a synthesis of this literature, which points at a robust positive link between recessions and the deterioration of mental health, including poor mental wellbeing, and increased rates of common mental disorders and suicides or suicide attempts. Following these observations, attention to the skies during recessions may be indirectly linked to changes in mental health. Our findings, however, depart from this literature in various central ways. First, we point at a robust positive link between wealth and the extent of UAP reports at the cross-section. Second, we illustrate that the magnitude of the main patterns we find, including the counter-cyclicality of reports across time, increases with the income decile. Third, we show that the impact of tightening economic policies is negatively associated with the extent of reports. These findings point at

[12] Prominent examples in the U.S., among many others, include recent CNN, Fox News, and MSNBC News interviews with the former director of the U.S. CIA, John Brennan, the former chair of the U.S. Congress Intelligence Committee, Senator Marco Rubio, and the former Senate majority leader, Senator Harry Reid, all openly acknowledging the relevance, legitimacy, and importance of this topic to U.S. national security. Further acknowledgements were given in recent public U.S. Congressional hearings, as well as by a NASA study on the topic, both undertaken over the course of 2022-2023. It is also worth noting the front-page story in the New York Times on this topic, published on Dec. 16th 2017 (available at: https://www.nytimes.com/2017/12/16/us/politics/pentagon-program-ufo-harry-reid.html), which exposed the Pentagon's efforts to investigating this issue and provided extraordinary evidence by U.S. naval pilots, thus marking the starting point of the shift in public acknowledgement.

[13] In a recent interesting application of UAP sightings data, Kitamura (2022) investigates the political consequences of unidentified threats.

opposite directions than those indicated in the noted literature, which link the deterioration of mental health to poor economic conditions and performance, and strengthens our proposed link to public attention. In addition, the analysis illustrates that the main results are robust to controlling directly for the extent of mental health, by considering county-level suicide rates. Last, sociological and psychological studies that examined the personal and social characteristics of UAP reporters (e.g., Zimmer, 1984; Patry and Pelletier, 2010) found no statistically precise difference in their mental conditions compared to individuals who did not report unusual observations in the skies.

Last, our study also relates to behavioral concepts of attention drawn primarily from the psychology and marketing literatures (a recent review of this literature is given by Loewenstein and Wojtowicz, 2023). First is *limited attention* (Gabaix, 2019), which suggests that when individuals' attentional capacity is stretched they may miss on information that would otherwise be captured. Findings in this literature indicate that attentional capacity increases with income (e.g., Banerjee and Mullainathan, 2008), and that attention to marginal tasks complements that given to key tasks (e.g., Schmitt and Schlatterer, 2021). We observe similar patterns via our proposed attention measure; namely, attention to the skies increases with income at the cross-section, and complements the attention given to the economy. Second is *inattentional blindness* (Redlich et al., 2020), which describes the extent to which unexpected events go unnoticed in the midst of other concurrent events. Given that anomalies in the skies occur unexpectedly, our study provides novel results on variations in inattentional blindness and their relation to economic conditions. Third is *load theory* (Murphy et al., 2016), which suggests that the extent of attention is dependent on perceptual load. To the extent that perceptual load can increase at times of employment, our results support the load theory hypothesis given the higher levels of attention we document during economic downturns.

3. Data

Our main analysis applies three main types of datasets. The first type is our novel dataset on UAP sightings. The second dataset includes U.S. macroeconomic and meteorological variables at both aggregate and regional (county) levels. The third dataset is documentation of lockdowns and restrictions used for the COVID-19 experiment. In this section we describe the first two, as they form the baseline panel adopted in the initial and main analyses. We describe the third dataset separately in the sub-section that outlines the COVID-19 analysis. Appendix tables A.1 and A.5 provide summary statistics.

3.1 UAP sightings

Our unique dataset on UAP sightings in the U.S. is derived from the NUFORC organization, which represents the prominent establishment in the U.S. that receives and documents reports from individuals across the country (and occasionally also from other countries). Individuals who observe phenomena in the sky which they cannot identify report it to NUFORC, either through the phone or via NUFORC's website.[14] Each report (observation) includes date, time, location, and a summary of the observation. The documentation, covering all reports, is organized and maintained by NUFORC, and is publicly available at NUFORC's website. Notably, NUFORC is considered the premier establishment for reporting such phenomena not only among the public, but also among professionals; the protocols of official organizations, such as the FAA, refer observers to NUFORC for filing a report in case of an unidentified observation in the sky. The latter strengthens NUFORC's standing as a legitimate, official central hub for data on UAP reports. Importantly, previous investigations of NUFORC's reports indicate that, consistent with the reports of governments and organizations noted earlier, the vast majority of reported observations are explained away by natural phenomena, with only a small fragment remaining unidentified (Costa and Costa, 2021).

NUFORC initiated systematic documentation of reports in the mid-1990s, after their website was established (before that reports were handled and recorded manually, starting in the 1970s). To gain even more reliability, we restrict the analysis to data since the 2000, which marks the start of a period in which the quality of online reports and data handling improved significantly (Costa and Costa, 2021). Our analysis considers only the number of reports, focusing on their time stamp and location, and ignores the accompanying description of observations. Using the location and date of observations, we manually construct a daily-level panel of observations, across U.S. counties, covering the period 2000-2020. Throughout the analysis we undertake different aggregations of this panel, at the regional or time levels (i.e. at the state or national levels, or adopting different time frequencies, such as annual or quarterly based ones, depending on the described exercise in the analysis and the availability of additional variables. For robustness, we limit the period to 2000-2017 in our main analysis, and extend it only in time-series analysis (e.g., examinations at the national level) with small number of observations. We do so because 2017 marks the shift in U.S. public opinion towards UAPs, primarily due to the front-page story at the New York Times published that year (noted in Section 2), which may potentially give rise to an implicit sample selection bias.[15] Overall, our panel covers about 70,000 UAP observations across more than 3,000 U.S. counties (see also Appendix Figure A.1 for summary statistics).

Figure 1 shows the monthly number of reports over time all around the U.S. Roughly several hundreds of reports are received in each month. Clearly, there is a strong seasonal component in the data series, where more UAP sightings are generally reported under good weather conditions, in the summer months. The low frequency variation is more interesting because it does not demonstrate a

[14] Notably, the NUFORC database is independent of the media, mitigating concerns related to reporting observations for purposes of public relations, media coverage, and potential tourism.
[15] Nonetheless, our main results are robust to examinations of extended samples, as also indicated via the detailed analysis of the more specific 2019-2020 period, discussed in Section 5.

simple increasing trend. Rather, there is a modest decline in the mid-2000s. Then, following the Great Recession, there are several years of a sharp increase. But this trend is completely reversed during the recovery years of 2014-2019. A sharp increase in reports on UAP sightings occurs again, beginning about a year before the burst of the COVID-19 crisis, and reaching a peak in April 2020 - the month of the first and most severe lockdown. However, this peak is still smaller than the former peak, which occurred in 2014. Finally, notice the strong reversal after April 2020, bringing the numbers a year afterwards back to the pre-increase levels. The big cyclical swings observed in Figure 1 suggest that varying factors may have a strong effect on the phenomenon of UAP sightings. Specifically, it seems that there is some counter-cyclicality with respect to U.S. economic business cycle. Thus, attention to UAPs seems to increase following recessions and to decrease during times of economic booms.

Importantly, we can also examine the geographical dispersion of reports, based on the documented location. The location includes a city and a U.S. state. As noted, we use this information to cluster the data at the county level, in addition to its state affiliation. Figure 2 shows a map describing the clustering of the reports for 2000-2017 at the county level. The main impression from the figure is that reports on UAP sightings are more common in populated and relatively wealthier counties. Interestingly, the possibility of a positive correlation with wealth across counties seems at odds with the counter-cyclical time variation described above. In the following analysis, we closely investigate these patterns and show how they can support the interpretation of the UAP sightings data as an indicator of the public attention. The analysis below will mostly rely on the panel structure of the data. Due to the availability of economic data, we will apply annual frequency at the county level, quarterly frequency at the state level, and monthly frequency at the national level. In the COVID-19 experiment we will be able to exploit the daily frequency of the data, as we describe later.

3.2 Economic and control variables

We supplement our panel with various economic and meteorological data, which enter the analysis as either outcome or control variables. Economic data is taken from the U.S. Bureau of Economic Analysis. We mostly use standard income, employment and GDP data which, for the post-2000 period, is available at the U.S. national level up to monthly frequency, at the U.S. state level up to quarterly frequency, and at the U.S. county level up to annual frequency. We also use several demographic variables, mainly population and density, at the appropriate levels. In our examinations of the effects of monetary policy, we in addition use data on monetary shocks, taken from Nakamura and Steinsson (2018) and Jarocinski and Karadi (2020). We outline further details on these shocks separately, in the corresponding sub-section.

Examining the attention given to the skies, we are also crucially required to control for visibility via weather conditions at the appropriate geographical level and time frequency. Hence, we complement the above data with a number of standard measures of weather conditions compiled by the U.S.

Department of Commerce using raw data from the National Oceanic and Atmospheric Administration. These data on weather conditions include the average minimum and maximum temperatures, as well as precipitation and snow levels, and are available for the geographical locations and time frequencies relevant for our analysis. Appendix Figures A.1-A.3 provide choropleth maps of the data. See also Appendix Table A.1 for summary statistics.

In our robustness checks, we use three additional variables: (i) As a control for the possible effect of mental health, we apply county-level data on suicide rates from the Center for Disease Control and Prevention (CDC). (ii) As a control for a possible effect of military installations we apply data from Kitamura (2022);[16] (iii) As an instrument for exogenous variations in attention we apply data on counties with booming shale formations from James and Smith (2017).[17]

4. UAP sightings and economic conditions

We seek to examine whether patterns of UAP reports have economic roots, and may be plausibly interpreted as representing more general patterns of public attention. Hence, as a first step, we examine the correlation between the phenomenon of UAP sightings and the economic environment. For this purpose, we exploit the variation in both the geographic domain and the time domain, which is available in the NUFORC dataset of UAP sightings.

Figure 3 provides a preliminary indication on the role of the geographic domain. The figure focuses on U.S. counties that are at the top percentile of UAP sightings. Specifically, it shows the number of UAP sightings reported in those counties over the period of 2000-2017, as well as the population and per-capita income deciles of those counties, relative to population and income distributions across all U.S. counties. As it might be expected, the leading counties in UAP sightings are highly populated. Yet, it also turns out that those counties are also wealthier, where two thirds of them belong to the 8-10 deciles of the income distribution. Examining the time domain though provides a different impression. Looking again on Figure 1, which describes UAP sightings in the U.S. over time, it seems that that the variation tends to be counter-cyclical. Hence, the relation between UAP sightings and income should be negative, rather than positive. In contrast to the time variation, the cross-sectional variation reveals a positive link between UAP sightings and economic conditions.

The complicated picture indicated by the raw data calls for a more formal empirical analysis. Thus, for location *i* and time *t*, we estimate specifications of the following form:

[16] We thank Shuhei Kitamura for kindly sharing his data. The data is based on geographical locations of military installations in 2008 from the US Census Bureau.
[17] Shale formations are defined as booming if they attributed to at least 1% of the increase in either tight oil or shale gas production observed from 2000 to 2012. The original source of the raw data is the Energy Information Administration. See more details in James and Smith (2017).

$$UAP_{it} = \alpha_i + \mu_t + \beta ECON_{it} + \boldsymbol{\delta} \boldsymbol{X}_{it} + \epsilon_{it} \ , \tag{1}$$

where UAP_{it} is the number of UAP sightings, α_i and μ_t are geographic and time fixed effects, $ECON_{it}$ is an economic variable and $\boldsymbol{X}_{it}$ is a vector of controls, which at the baseline includes population, density and a set of climate controls, such as precipitation and temperature levels. Our main interest is in the sign and significance of the coefficient β, which captures the sensitivity of UAP sightings to economic conditions.

Due to the structure of the data, the estimation can be applied to various geographic levels and time frequencies, with some tradeoff. Specifically, as noted, at the U.S. county level, economic data is available at annual frequency. At the U.S. state level, quarterly frequency can be used. Estimation at the aggregate U.S. level can use monthly frequency. Results for these three geographic levels are reported in Tables 1 to 3, respectively.

Table 1 reports county-level estimates, where the economic variable $ECON_{it}$ is personal income in county *i* on year *t*. The set of controls includes population (in logs), density (squared miles per person) and a set of weather variables (such as average temperature, precipitation, days of snow). Notably, the dependent variable is the number of UAP sightings without standardization. Since it is not obvious whether to standardize by population, area, or density, we employ them as controls. A first interesting finding is that all the estimates of β are significant. Thus, the phenomenon of UAP sightings is correlated with the level of income. Furthermore, the results in the various columns of the table highlight a striking change in the sign of the β coefficient.

The first two columns report between-county estimates. Column (1) presents cross-sectional estimates using county averages over the years. Column (2) presents panel estimates, but without fixed effects. In both estimations the effect of personal income on UAP sightings is significantly *positive*. However, in column (4), when fixed effects are added to the panel estimation, we obtain significant *negative* estimates for the within-county income effect. A similar difference in the sign of the β coefficient is obtained when the income variable is included with a lag or when adding a lag of the dependent variable (column (3) as opposed to (5) and (6)).

Hence, the results confirm the impression from the raw data, as described above. At the geographic domain, the phenomenon of UAP sightings is more prevalent in high income counties, as indicated by the positive β in the between-county estimations. However, within counties UAP sightings over time are negatively related to the level of income. This key finding points to two underlying forces that drives the phenomenon of UAP sightings, both being consistent with central findings in the empirical rational inattention literature, discussed in Section 2. The first type of force is a social force, which demonstrates a higher tendency to UAP sightings among the rich. The second type of force accounts for the time variation and demonstrates a correlation with a negative sign. The latter force, taken together with the former, can be interpreted by an attention channel. Higher levels of attention across wealthier regions, and over the business cycle during bad times, correspond to higher levels of attention to UAPs.

The change in the sign of β in between and within estimations is replicated for U.S. states, as described in Table 2. Compared to the county level analysis, the cross-section is substantially smaller, but we benefit from a higher frequency relative to the county level, by exploiting quarterly instead of annual data. Again, we document a significant positive correlation between UAP sightings and income when fixed effects are not included (columns (1) to ((3)). In column (1), the estimation is purely cross-sectional. The coefficient is positive but insignificant due to the small number of states. Columns (2) and (3) apply panel estimation. We added dummies for the calendar quarters as additional controls that account for seasonality. The coefficient estimates are positive and strongly significant. However, when focusing on the variation within states, the coefficient estimates become significantly negative (columns (4) to ((6)).[18] Hence, the evidence in Table 2 points again to the two forces underlying the phenomenon of UAP sightings.

Finally, Table 3 focuses on the time domain by bringing evidence based on data aggregated to the level of the entire U.S. Thus, specification (1) is estimated as a time series regression, without the cross-sectional dimension. While the number of observations drops dramatically, we can apply economic data with monthly frequency, available at the national level (in addition, we extend the sample period examined). Table 3 reports estimates of the effects of three macroeconomic variables on UAP sightings during the period of 2000M1-2021M4, adjusted for seasonality.

The estimates reported in columns (1) to (3) are all significant in the same direction. UAP sightings decrease in personal income (column (1)) but increase in unemployment rate (column (2)). UAP sightings are further negatively related to the Consumer Confidence Index (column (3)). These results are consistent with the correlation documented within U.S. counties and states, demonstrating an increase in UAP sightings during business cycle downturns. The significance of the Consumer Confidence Index is particularly interesting. The Consumer Price Index is a prominent forward-looking indicator, which builds on expectations reported in surveys of consumer opinions.[19] The fact that variations in economic outlook of consumers are related to variations in UAP sightings further facilitates the attention channel proposed above. Thus, a bad economic outlook perceived by consumers draws higher attention which is also reflected by more UAP sightings.

Finally, columns (4) and (5) add an important control – the time-series of UFO Google searches in the U.S., obtained from Google Trends (available since 2004).[20] This index can control for time

[18] In the within-state estimation fixed effects are included. Notice that the calendar quarter dummies are now redundant due to the quarterly fixed effects.

[19] For details, see OECD (2021), "Business tendency and consumer opinion surveys", *Main Economic Indicators* (database), https://doi.org/10.1787/data-00041-en.

[20] As noted, the term UAP was coined by the U.S. Pentagon only recently; hence, considering earlier years we consider the term UFO for the Google searches.

variation in the public interest in UAPs, driven by media events or other special events, such as the COVID-19 lockdowns.[21] In line with this conjecture, the effect of this variable is positive and significant, as reported in the table. Yet, the effect of the economic variable (income) is still significantly negative (column (5) adds lags).

Robustness checks. Appendix Tables A.2-A.7 provide additional supporting evidence for the two types of correlations with opposing signs between UAP sightings and economic conditions. In Appendix Table A.2, we document a particularly strong effect among high-income regions, which weakens the interpretation of the effect as an outcome of mental health impact driven by the poor. Appendix Table A.3 examines additional splitting of the sample, according to population, the number of UAP sightings and the sample period. Appendix Table A.4 applies employment and GDP per capita as alternative economic variables ($ECON_{it}$) in specification (1) and reports similar results. Appendix Table A.5 shows that the within-county negative effect stays significant when including state-by-year interaction effects in addition to the county and year effects, which control for cross-state differences across years, including for instance cultural or political differences that may affect the patterns of sky viewing and the extent of reporting.

To investigate more directly the possibility of a mental health channel, given the latter's association with economic conditions and hence its potential indirect link with UAP reports, we also augment specification (1) with data on suicide rates as a proxy for mental health. The literature has provided repeating evidence for an increase in suicide rates during recessions (e.g., Ruhm, 2000; Luo et al., 2011; Reeves et al. 2012). Thus, it is possible that UAP sightings increase in recessions due an increase in mental health problems, rather than an increase in attention. To control for this channel, we use U.S. county-level annual data on suicide rates from the CDC.[22] As reported in Appendix Table A.6, the effect of income over time within counties remains significantly negative, while the cross-county effect remains positive. Moreover, the table shows that the estimated coefficient on the suicide variable also takes opposing signs within and across counties. While within counties, the coefficient on suicides is positive, across counties it is negative. The cross-county negative effect is at odds with the idea that UAP sightings are driven by variations in mental health. Rather, the changing sign of the suicide effect is consistent with the negative correlation between suicides and economic conditions documented in the literature.

Lastly, we also control for the presence of military installations which are often associated with sightings of UAPs (Costa and Costa, 2021). Columns (1)-(3) in Appendix Table A.7 reports cross

[21] Appendix Figure A.4 describes this data. It can be noticed that the Google Trend is characterized by exceptional spikes, including for instance one in April 2020 during the COVID-19 lockdowns. However, it does not generally share the movements and trends of the UAP sightings reports. The notion that the extent of Google searches may be driven by media or special events is supported by evidence in previous studies (e.g., Fischer et al., 2020).

[22] The number of annual suicide cases at the county level is not provided by the CDC, if it is positive but below ten (due to confidentiality considerations). The estimation therefore excludes these observations.

sectional estimates with a controlling dummy variable which receives 1 for a county with a military installation (from Kitamura, 2022). The coefficient-estimate on the dummy variable is indeed significantly positive. Yet, the cross-sectional income effect remains significantly positive as well. In the within-county estimation that includes fixed effects the military installation dummy is interacted with the year effect. As in the baseline estimation, the sign of the income effect changes to negative.

In sum, the findings based on specification (1) highlight two economic forces, driving the phenomenon of UAP sightings in opposite directions. Geographically the phenomenon is stronger in high income areas. Yet, over the business cycle the phenomenon is stronger in downturns. The cross-sectional and time variations in UAP sightings reflect variations in the public attention. In the next section, we further explore the attention channel. Exploiting the COVID lockdowns as exogenous shocks to the public attention, we seek to facilitate a more causal link between attention and the phenomenon of UAP sightings.

5. UAPs and Public attention: The COVID experiment

The analysis so far pointed at a robust association between the extent of UAP reports and economic conditions, via conditional correlations and the adoption of standard time frequencies. In this section we seek to go beyond on both fronts; namely, establishing causality, and providing an application for the availability of daily frequency of the UAP data. To do so, we exploit a quasi-natural experiment affecting public attention, with daily variation – the case of COVID-19.

The outbreak of the COVID pandemic in the first months of 2020 can be viewed as an exogenous shock to public attention (see, e.g., Binder, 2020). COVID lockdowns artificially created ample new free time for individuals locked in their homes, freeing them from being absorbed in mundane tasks of everyday life, and thus affecting their level of attention to factors that under normal circumstances would go unnoticed. To the extent that UAP sightings provide a good proxy for the level of public attention, they should, therefore, respond significantly to this major shock. Indeed, it is easy to recognize the peak in UAP sightings reported to NUFORC during April 2020, which is described in Figure 1. Yet, the figure also shows a great increase already in 2019, before the pandemic. The peak of April 2020 was short-lived. Not only that the numbers declined to the pre-pandemic level in the following months, but there was a further dramatic drop at the end of the year, back to levels that precede the 2019 increase. Thus, the aggregate picture is not clear enough.

To assess the effect of COVID on UAP sightings and the role of the attention channel in this mechanism, we exploit the daily variation in the NUFORC data. Following the difference-in-differences methodology, this variation can be matched to daily variation in COVID lockdowns across U.S. counties, to draw inference about the causal link between unprecedented lockdowns and attention to

UAPs. In our setting, the treated groups are U.S. counties during different periods of time over 2020, in which they were under lockdowns with changing degrees of restrictions.

For the treatment data, we exploit a daily-level index on the extent of COVID lockdown restrictions by U.S. counties, derived from the U.S. CDC. This index provides categorial data that takes the values 1 to 7, where 1 is a stay-at-home order, 7 is no order in place, and in between lie various medium level orders, with a decreasing intensity in number (See Appendix Table A.8 for more details). Importantly, changes in this index are plausibly exogenous, as they are a consequence of regulatory reactions to pandemic patterns which were unforeseen to local regulators. We exploit the plausibly exogenous variation provided by this index to identify the causal impact on the extent of UAP reports.

Given the daily-level nature, and the difference-in-differences setting, of the analysis, we also include the year 2019 in the examined panel, as a pure-control year. Notably, in 2019 the examined index takes the value 7 (i.e., no restrictions) in all counties and days. Thus, we estimate daily-level specifications, covering January 1st 2019 to December 31st 2020, which take the following form, for county i at day t:

$$UAP_{it} = \alpha_i + \mu_{seas} + \delta GT_{t-1} + \boldsymbol{\gamma ORDER_{it}} + \epsilon_{it} \,. \qquad (2)$$

The design of specification (2) is in the spirit of the well-known two-way fixed effects specifications (TWFE), where α_i is a county fixed-effect and μ_{seas} captures seasonal effects using two sets of dummies for the calendar week and for the day of the week. GT_{t-1} is an aggregate trend control, using the Google Trends data, as in the previous section (available at a weekly frequency). Our main interest is in estimating the effect of $\boldsymbol{ORDER_{it}}$, which represents the outlined CDC index. In effect, $ORDER_{it}$ represents a set of dummies that take the value of 1 if county i is under a certain type of COVID orders at day t. We group the abovementioned seven restriction-categories to three groups that account for the bulk of variation in the data (each named based on the index categories it covers). $ORDER_{it}\ 1-2$ captures severe lockdowns, $ORDER_{it}\ 3-5$ captures medium-level restrictions and $ORDER_{it}\ 6-7$ captures times of very light or no restrictions. The regression includes $ORDER_{it}\ 3-5$ and $ORDER_{it}\ 6-7$, so that the coefficients measure the effect relative to a state of a lockdown ($ORDER_{it}\ 1-2$).[23]

The results of several versions of specification (2) are described in Table 4. In line with the attention effect of the COVID lockdowns, we get negative estimates for the coefficients on $ORDER_{it}\ 3-5$ and $ORDER_{it}\ 6-7$, implying a decline in UAP sightings relative to days of lockdowns. Once the fixed

[23] The design of specification (2) resembles a treatment with staggered adoption, recently discussed by the DiD literature. As pointed by several studies (Athey and Imbens, 2021, Callaway and Sant'Anna, 2021, Goodman-bacon, 2021, Sun and Abraham, 2021), the variation in treatment timing in this setting may lead to inappropriate weighting of the treatment effect by the standard TWFE estimator. Our setting is further complicated by variation in the level and the ending time of the treatment (different levels and ending dates of COVID restrictions). Nevertheless, our focus in the current exercise is only on detection of an effect and not in providing a meaningful quantification for policymakers.

effects are introduced the two coefficients are highly significant (columns (2) to (5)). The coefficients are still significant, even when accounting for the high public interest in UAPs during lockdowns, using the Google Trends variable (column (5)). Notice also that the coefficients on both $ORDER_{it}$ $3-5$ and $ORDER_{it}$ $6-7$ have a similar size, especially after including the Google Trends control. Thus, the attention effect on UAPs is mainly demonstrated during the severe lockdown restrictions (the base dummy, $ORDER_{it}$ $1-2$).

To shed more light on the dynamics of the response of UAP sightings to the lockdowns, we also adopt an Event Study design, by estimating the following specification:[24]

$$UAP_{it} = \alpha_i + \mu_{seas} + \delta GT_{t-1} + \sum_{k=-3}^{16} \gamma^k LOCKDOWN_{it}^k + \epsilon_{it} \,. \qquad (3)$$

Specification (3) focuses on the lockdowns, based on the above results and estimate their dynamic effect on UAP_{it}, using the daily dummies $LOCKDOWN_{it}^k$. The variable $LOCKDOWN_{it}^k$ is a dummy that takes 1 for the kth day before (negative) or after (positive) the beginning of a lockdown, defined by the CDC order categories of 1 or 2. For $k = 16$, the dummy takes 1 for any day of lockdown from the 16th day onward. Thus, the coefficients γ^ks summarize the daily effect of the lockdown relative to "normal" days (days with CDC order categories 3-7 which are at least 4 days prior to a lockdown).

Using the same daily data for 2019-2020, Panel A of Figure 4 describes the estimates of γ^k over k (horizontal axis), with 90% confidence intervals. Interestingly, the Figure shows a very gradual increase in UAP sightings, following the starting day of the lockdown ($k = 0$. The pre-trends coefficients are also insignificant). Only after 10 days the effect becomes more noticeable and significant. The significant effect continues even after the 15th days, as indicated by the γ^{16} estimate. The relatively slow but significant response, documented in the figure, seems to be more consistent with the attention channel, where attention gradually propagates in the public as the lockdown restriction continues. If the interest in UAPs was driven by the unusual events or by greater visibility conditions induced by lockdown restrictions (on traffic, industry and so on), we should expect to have seen a more sudden increase, right after the lockdown beginning.

Finally, Panel B of Figure 4 provides a placebo test by estimating specification (3) using only the data of 2019 and imposing the same dates of the 2020 $LOCKDOWN_{it}^k$ as a counterfactual. The figure describes a non-trending graph of insignificant estimates (except one), thus supporting the lockdown propagating effect presented in Panel A.

In sum, the COVID exercise strengthens the interpretation of the UAP sightings data as an indicator for the public attention and rationalizes the correlations with economic conditions, documented in the

[24] The event study design is also particularly recommended in a setting like COVID, in which heterogeneity in treatment effect is expected. The heterogenous effect is also related to the issue of staggered adoption mentioned in the previous footnote (see Goodman-Bacon and Marcus, 2020).

previous section. Building on this interpretation, in the section we first compare this measure to other standard ones offered in the literature; thereafter, we propose a macro application for this novel data, in which variations in attention can address regional variations in the transmission of monetary policy in the U.S.

6. UAP Sightings VS. Existing Attention Measures

The evidence in the previous sections demonstrate that the pattern of UAP sightings is correlated with economic conditions. Interestingly, this correlation goes in opposite directions. While UAP sightings are more prevalent in high-income regions, the pattern over time within regions is counter-cyclical, pointing at an increase during bad economic times. Interpreting UAP sightings as a measure of attention can resolve this evidence. In line with existing evidence on patterns of attention, as noted in Section 2, agents with stronger socioeconomic background are better informed on macroeconomic conditions and have smaller expectations errors, while over time attention to information is increasing in recessions. The sensitivity of UAP sightings to the attention shock in our COVID-19 exercise points further in the direction of the attention interpretation.

In this section we pursue this interpretation by comparing the UAP sightings measure to direct measures of economic attention. For this purpose, we apply two closely related direct measures proposed by Coibion and Gorodnichenko (2015) and Goldstein (2023). Both measures directly estimate parameters of inattention in models of expectations formation with information frictions, using forecast data from surveys. While the first measure is based on mean-level forecasts, the second measure is based on individual-level forecasts. To fix ideas, we briefly show how these measures are derived from a simple noisy information setup. Suppose that a fundamental x_t follows AR(1) process and individuals receive signals about the state with idiosyncratic noise. Formally, this simple setup is described by the following state-space representation:

State: $x_t = \rho x_{t-1} + v_t,$ (4)

Measurement: $y_t^i = x_t + \omega_t^i,$ (5)

where $v_t \sim iid\ N(0, \sigma_v^2)$ is the shock to the fundamental x_t and y_t^i is a signal, received by individual i at time t about the fundamental, that contains an individual-specific noise $\omega_t^i \sim iid\ N(0, \sigma_\omega^2)$. Agents process the noisy signals with a Kalman filter. The optimal forecast of the individual for h steps ahead is derived by the Kalman filter:

$$\begin{aligned} x_{t+h|t}^i &= \rho^h x_{t|t}^i = \rho^h \left[x_{t|t-1}^i + G\left(y_t^i - x_{t|t-1}^i\right)\right] \\ &= (1-G)x_{t|t-1}^i + G\rho^h y_t^i, \end{aligned} \quad (6)$$

where G is the (steady-state) Kalman gain determined by the signal-to-noise ratio and the persistence of the fundamental. It is clear from equation (6) that the optimal forecast is a weighted average of old information, captured by the revised forecast $x^i_{t|t-1}$ and new information in signal y^i_t. Thus, the Kalman gain, as a weight placed on new information, is treated as a measure of attention, while $(1-G)$ is a measure of inattention.

Averaging equation (6) across individuals ($x_{t+h|t}$ is the average of $x^i_{t+h|t}$) and using the state equation (4), Coibion and Gorodnichenko (2015) obtain the following specification for estimating inattention:

$$x_{t+h} - x_{t+h|t} = \frac{1-G}{G}\left(x_{t+h|t} - x_{t+h|t-1}\right) + \varepsilon^i_t \qquad (7)$$

This specification relates ex-post forecast errors to ex-ante forecast revisions at the aggregate level. Although forecasts are formed rationally, the gradual adjustment to new information as expressed in equation (6) leads to forecast error predictability at the aggregate level, where on average the mean forecast is gradually revised towards x_{t+h}. The coefficient on the mean forecast revision captures the degree of information rigidity or the level of inattention.

Alternatively, Goldstein (2023) derives from the same forecasting rule in equation (6) a specification that applies to the individual-level forecasts:

$$x^i_{t|t} - x_{t|t} = (1-G)\left(x^i_{t|t-1} - x_{t|t-1}\right) + \varepsilon^i_t \qquad (8)$$

Specification (8) shows that the level of inattention $(1-G)$ directly maps to the level of persistence in the deviation of the individual forecast from the mean forecast. Intuitively, since forecast dispersion is driven by heterogenous information, the persistence of forecast dispersion is determined by the degree of information rigidity, and thus can measure the level of inattention.

Using forecast data, we estimate the two specifications (7) and (8) and obtain two measures of inattention that can be compared to the measure of UAP sightings. Recall that the measure of UAP sightings varies both over time and across U.S. regions. Thus, a full comparison can be done if forecast data vary in a similar way. However, cross-sectional variation in forecast data is not available, which is an important motivation for using the measure of UAP sightings as a proxy for attention, instead of the conventional above measure. To further assess how informative is the unconventional proxy, we will compare it to the conventional measures based on the time dimension.

To produce time-varying coefficients from the mean-level specification (7), we follow Coibion and Gordnichenko (2015) and pool forecasts of different variables. We use forecast data for all macroeconomic variables available in the well-known Survey of Professional Forecasters (SPF) ran by the Philadelphia Fed. For each quarter during 2000-2021 period, we estimate the coefficient in specification (7), using forecast data from the last eight quarters.[25] Panel A in Figure 5 compares the time-varying estimates with eight-quarters moving average of the number UAP sightings. Strikingly, the forecast-based measure of inattention demonstrates variations over time which are the opposite of variations in UAP sightings. Quantitatively, the correlation over time is -0.211 and significant at the 5% level.

Panel B documents even a stronger negative correlation (-0.543) of the UAP sightings measure with the forecast-based measure estimated by the individual-level specification (8). The time-varying estimation of specification (8) has much greater statistical power relative to specification (7) since it uses individual-level forecasts. Further, it is not sensitive to a public information bias and behavioral forms of bias that may distort the results from the mean-level specification, as shown in Goldstein (2023). These important advantages make specification (8) a better measure of expectations – based attention relative to specification (7). Thus, the comparison in Panel B considerably strengthens the interpretation that movements in UAP sightings may represent variations in the level of attention.

Furthermore, by using individual level forecasts, specification (8) can produce time-varying estimates of inattention for different macroeconomic variables in the SPF survey. Thus, we can examine what are the macroeconomic variables for which inattention patterns are the most similar to the patterns of UAP sightings. We therefore estimate specification (8) quarter by quarter for each SPF variable and report in Table 5 the correlation over time for each variable with the UAP sightings measure. Interestingly, we document the strongest negative correlation of UAP sightings with inattention to the broadest measures of macroeconomic activity – both nominal and real GDP. Negative correlation is also documented with respect to interest rate, especially the long-run rate. By contrast, there is a significant positive correlation with respect to CPI inflation, which is consistent with a tendency to allocate less attention to inflation during economic slowdowns that are typically associated with lower inflation. Hence, the breakdown of the inattention measure based on specification (8) by different macroeconomic variables reveals that variations in UAP sightings overtime corresponds to variations in attention to the general state of the economy.

Following this additional evidence for the interpretation of the UAP sightings measure as a proxy for variations in public attention to economic conditions, we next propose an application of this measure that also exploits the geographic dimension of our data. The application we study in the next section explores the implications of regional heterogeneity in the level of attention to the conduct of monetary policy.

[25] In effect, we extend the Coibion and Gordnichenko (2015) measure such that it corresponds to our extended sample period, using their methodology and updated underlying data.

7. UAP Sightings and Monetary Policy Transmission

In this section we propose a novel application of the UAP sightings data as a measure of economic attention. Our conjecture is that, by measuring attention, UAP sightings can account for both regional and time variation in the response to macroeconomic shocks. We focus on monetary shocks, for which the attention channel has been recently explored in the literature (albeit at the national level). Higher levels of attention are associated with weaker effects of monetary shocks since the public is more aware to monetary decisions (e.g., Maćkowiak et al., 2023). This channel can account for recent evidence of business-cycle variation in both the attention to information and the effect of monetary shocks. Specifically, as noted, in recessions estimated attention tend to increase (Coibion and Gorodnichenko, 2015; Song and Stern, 2021; Flynn and Sastry, 2021) and the estimated effect of monetary shocks is lower (Tenreyro and Thwaites, 2016). Along the same lines, if UAP sightings capture variations in economic attention it is expected to account for the varying effects of monetary policy. Moreover, it can further account for a new type of regional heterogeneity in the effect of monetary policy, which is driven by heterogenous attention. This heterogeneity can also be a key to understanding why UAP sightings are positively correlated with income at the cross-sectional level.

To pursue our conjecture, we employ a local-projection specification (a' la Jorda, 2005) and estimate the varying effect of monetary shocks at the regional level. Using U.S. regional data, we estimate specifications of the form:

$$y_{it+h} - y_{it} = \alpha_{ih} + \mu_{th} + \beta_h UAP_{it} \varepsilon_t^m + \boldsymbol{\Gamma}' \boldsymbol{X}_{it} + e_{ith}, \qquad (9)$$

where y_{it} is an economic outcome variable, and α_{ih} together with μ_{th} are regional and time effects that absorb fixed regional heterogeneity and common trends, respectively. $\boldsymbol{\Gamma}'\boldsymbol{X}_{it}$ controls for lags of the outcome variable. Our focus is on the interaction term $UAP_{it}\varepsilon_t^m$ where UAP_{it} is a standardized measure of UAP sightings per capita in region i at time t,[26] and ε_t^m is a U.S.-level monetary shock. Thus, the coefficient β_h captures variations in the effect of the monetary shocks which are driven by variations in our UAP sightings measure, across and within U.S. regions (h denotes the horizon of the projection).

Data availability on UAP sightings limits the period of estimation, while data availability on economic outcomes limits the frequency. Consequently, we estimate specification (4) with state-level data at the quarterly frequency for the period of 2000Q1-2017Q4 ($t + h$). For the outcome variable, we use state-level data on the log of GDP per capita, employment per capita or the rate of unemployment. The data on y_{it} and UAP_{it} is seasonally adjusted. We further use state-level data at the annual frequency, for which consumption data can also be used as an outcome variable (log of per capita consumption). The specification is also estimated at the annual frequency using county-level data for the period of

[26] Unlike previous analysis of the determinants of UAP sightings, in which we control for population on the right-hand side of the specification, here we use UAP sightings as a measure of attention and thus apply a per capita measure.

2000-2017. Two of the above outcome variables are available at the county level: GDP and employment.

For the monetary shock, ε_t^m, we use a high-frequency measure, following Gurkaynak et al. (2005), which is extensively applied in recent work (e.g., Gorodnichenko and Weber, 2021; Nakamura and Steinsson, 2018). We take the most extended series from Acosta and Saia (2020). This approach identifies monetary shocks as a change in the Federal Funds rate implied by Federal Funds future contracts, in a narrow window of time around FOMC announcements. Usually, there are two announcements in each quarter. We apply a summation over time to match with the frequency of the specification (quarterly or annual). A one-unit shock corresponds to a change of the Federal Funds rate by 100 basis point.

The results for the interaction coefficient are presented in figures 6, 7 and 8. Figure 6 shows the estimates of β_h from 0 to 8 quarters after the shock, based on the U.S. state-level data. 90% confidence interval is denoted by the shaded area. The estimates reveal a dependency of the impulse-response to monetary shocks on UAP sightings, in line with our conjecture. The accumulated response of GDP and employment depends positively on the level of UAP sightings, while the response of unemployment rate depends negatively. The effect is mostly significant for the (un)employment outcomes. Because the baseline effect of a monetary shock on the economy is negative (i.e., a shock with a positive sign represents a contractionary rise in interest rates), these findings imply that a high level of UAP sightings *mitigates* the effect of monetary policy, in line with the attention interpretation.

Replicating the estimation at the annual frequency, we obtain estimates in the same direction for four outcome variables, as presented in Figure 7 (h runs until 4 years after the shock). The estimates are generally insignificant, though, at this lower frequency (recall the short period of time due to availability of data on UAP sightings). Interestingly, the estimates are significant for the response of GDP at longer horizons, despite the insignificant estimates at shorter horizons in the previous quarterly estimation.

Finally, estimates at the county level are reported in Figure 8. Here we obtain positive estimates of β_h for the response of both GDP and employment, which again points to a moderation of the effect of monetary shocks due to higher attention, as captured by the measure of UAP sightings. Relative to the state-level results at the annual frequency in Figure 7, and despite the short time span, the regional disaggregation to counties brings about a notable significance of the estimates, especially for the response of employment.

The various estimates also indicate that our attention measure accounts for an heterogenous effect which is economically important. For example, at the county level the impulse response of GDP and employment to 100 basis point change in the Federal Funds rate goes to 0.1. Thus, an increase of one standard deviation in the UAP sightings indicator implies that the annual impact of a 25 basis points change in the Federal Funds rate on local GDP and employment is *weaker* by 2.5 percentage points.

Overall, the results from specification (4) confirm that the measure of UAP sightings provides a meaningful economic indicator, which can track the state of public attention. Notably, this unconventional measure is able to capture a new type of regional variation in the effect of monetary policy, which cannot be estimated by conventional economic measures. The results can further shed light on the cross-sectional heterogeneity documented in the previous sections: regions with high level of attention tend to be wealthier because they respond better to macroeconomic shocks. Despite this regional heterogeneity the trend over time is similar, where attention tends to increase during business-cycle downturns.

7.1 Robustness checks

Appendix Figures A.5-A.9 report additional results from several robustness checks. First, dealing with the monetary shocks, we employ the HFI monetary shocks from Jarocinski and Karadi (2020) in Appendix Figure A.5. While the above measure is based on changes in the short-term Federal Funds rate, the monetary shocks of Jarocinski and Karadi (2020) are based on the first principal component of several interest rates. Most importantly, they also apply a decomposition that extracts information effects in the central bank announcements. Thus, the figure further shows that the impulse responses stay similar after accounting for the information effect.

Second, we allow the impulse-response specification to distinguish between monetary shocks with positive (contractionary) and negative (expansionary) signs. While some difference is documented at the state level (Appendix Figure A.6), it is not systematic across the different variables in the figure panels. Furthermore, the results are very robust at the county level (Appendix Figure A.7), with similar impulse responses for contractionary and expansionary shocks.

Third, dealing with the sample period, we verify that our results hold when omitting the quarters around the onset of the financial crisis between 2008Q3 to 2009Q2 (Appendix Figure A.7). Fourth, dealing with controls, we omit the time effects, which allows us to explicitly consider the average effect of the monetary shock ε_t^m in the specification, as well as additional aggregate controls $\boldsymbol{X}_t$ at the U.S. level (lags of inflation rate, GDP growth, and unemployment rate). The results in Appendix Figure A.9 are similar to our baseline findings.

Our last robustness check applies an Instrumental Variable approach to address concerns about the endogeneity of attention. While the weather controls are naturally a source of exogenous variation in the UAP sightings measure, they are not appropriate instruments for attention. The level of attention can be high, even if UAPs cannot be observed due to bad weather conditions. Instead, to instrument attention we use exogeneous, cross-sectional and time, variation in natural resource abundance. Our idea is that in areas abundant in oil the level of economic attention would vary differently in response to changes in oil prices, as the latter represent plausibly exogenous income shocks (e.g., Raveh and Tsur, 2020). Using county-level data from James and Smith (2017), the exogenous variation in oil resources is measured by a dummy that equals 1 for counties with a "booming" shale formation. We find that the interaction of this dummy with the log change in oil prices (WTI) has a negative effect on UAP sightings.[27] Thus, UAP sightings in oil-rich counties increase (decrease) in response to a decrease (increase) in oil prices, which is consistent with the attention interpretation where attention gets higher (lower) in downturns (booms). This "first stage" finding therefore supports the validation of the interaction as an instrument for attention.[28] Appendix Figure A.10 replicates the county-level local projections in Figure 8, using IV estimation. The results demonstrate again a mitigated response to monetary policy for higher levels of the UAP measure of attention.

8. Conclusion

Public attention takes a critical role in macroeconomic analysis; however, measuring it for different geographical boundaries and locations, as well as for different time frequencies, has been a limitation of the currently available, standard measures. To fill this gap, this paper offered a novel measure of public attention, based on the attention given to the skies, and its potential complementarity to the attention provided to economic information. This type of attention, we argued, can be measured via the extent of UAP reports.

To examine this hypothesis, we constructed a (baseline) daily-level panel of UAP reports across U.S. counties, for the post-2000 period, using the location and time stamp of UAP observations recorded by NUFORC, a major hub of UAP sightings records in the U.S., and the first contact of individuals (non-officials, and officials alike) seeking to report an unusual observation in the skies. Importantly, the features of the UAP records, including their (city-level) location and date, uniquely enables offering a macro-level proxy for public attention that can be aggregated to different geographical levels as well as different time frequencies, up to the daily level. We exploited these features in our analysis, and demonstrated applications of them.

As a first step, our analysis established a robust correlation between economic conditions and the extent of UAP reports, controlling for visibility, via weather conditions, and a multitude of external influences, including the extent of Google searches, mental health, and military installments, among

[27] We first regress UAP sightings on weather controls population and density to remove sources of variation which are unrelated to attention. We then regress the (standardized) residuals on the booming dummy and the interaction of the dummy with the change in oil prices.

[28] The F-statistic from the "first stage" regression is 19.69. However, note that when applying the IV to the local projection specification in (9) the technical first stage instruments the interaction of UAP sightings with the monetary shock $UAP_{it}\varepsilon_t^m$. Specifically, we instrument $UAP_{it}\varepsilon_t^m$ by the interaction $oil_{it}\varepsilon_t^m$ and by oil_{it}, where oil_{it} is the oil resource dummy multiplied by the annual log change in oil price.

others. Examining the U.S. case at various levels, including national, state, and county, pointed at similar robust patterns. At the cross-section we noted a positive association between economic conditions and UAP reports intensity; conversely, within-regions across time, we observed counter-cyclical patterns. Motivated by the reported patterns of previous, standard measures of attention, exhibiting similar behaviors, we interpreted these robust patterns of our indicator as pointing at the extent of public attention. To further establish this interpretation, and also provide an application of the unique daily-level frequency of our proposed indicator, we examined the impact of plausibly exogenous daily-level shocks to public attention, via the extent of county-level COVID lockdown restrictions over the 2020 period (versus the 2019 period as control), on the extent of UAP reports. We found a robust positive impact of the extent of lockdowns on that of UAP reports, thus establishing causality, and reaffirming the patterns observed via the conditional correlation analysis, as well as the consequent interpretation of measuring the extent of public attention.

We further compared our measure to previous conventional measures of attention and documented a strong correlation, Thereafter, we provided an application of our measure as a novel proxy of public attention via an examination of the heterogeneous reactions to monetary policy shocks. Our main finding is that the impact of monetary policy is robustly and significantly mitigated in counties with greater extents of UAP reports, consistent with the expected impact of corresponding variations in the extent of public attention.

Our analysis, therefore, proposes and demonstrates the applicability of a novel measure of public attention that enables accounting for rational inattention in empirical macroeconomic analyses of different geographical levels and locations, as well as different time frequencies. Noting the central role of public attention in macroeconomic fluctuations, illustrated by the recently emerging related literature, our proposed measure may, thus, have various potentially central implications for macroeconomic analyses and policy design.

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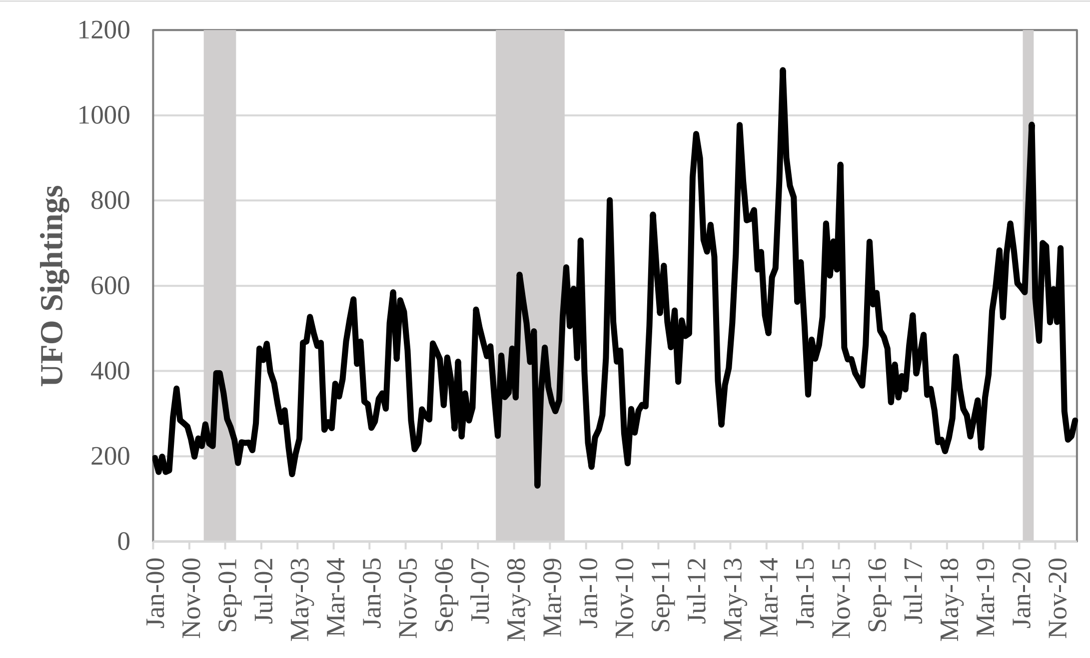
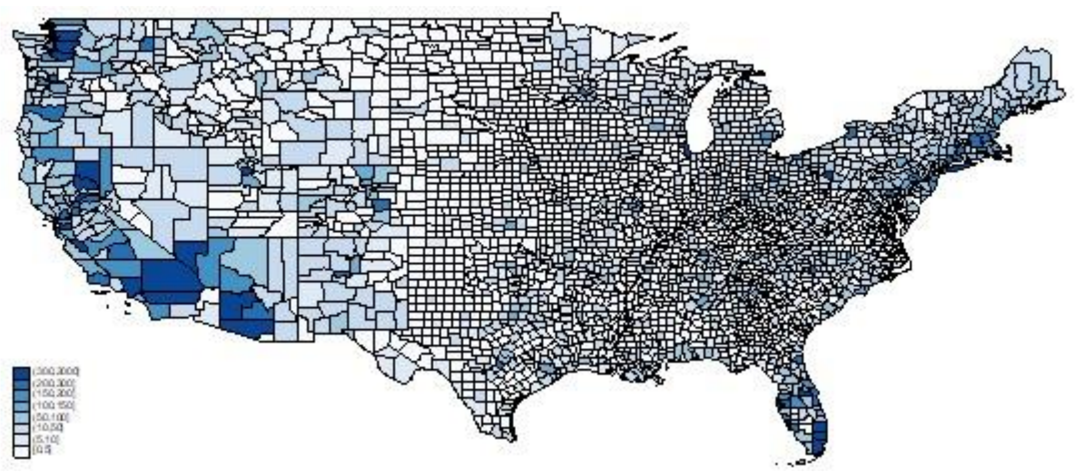
Figure 1: UAP Sightings in the U.S.



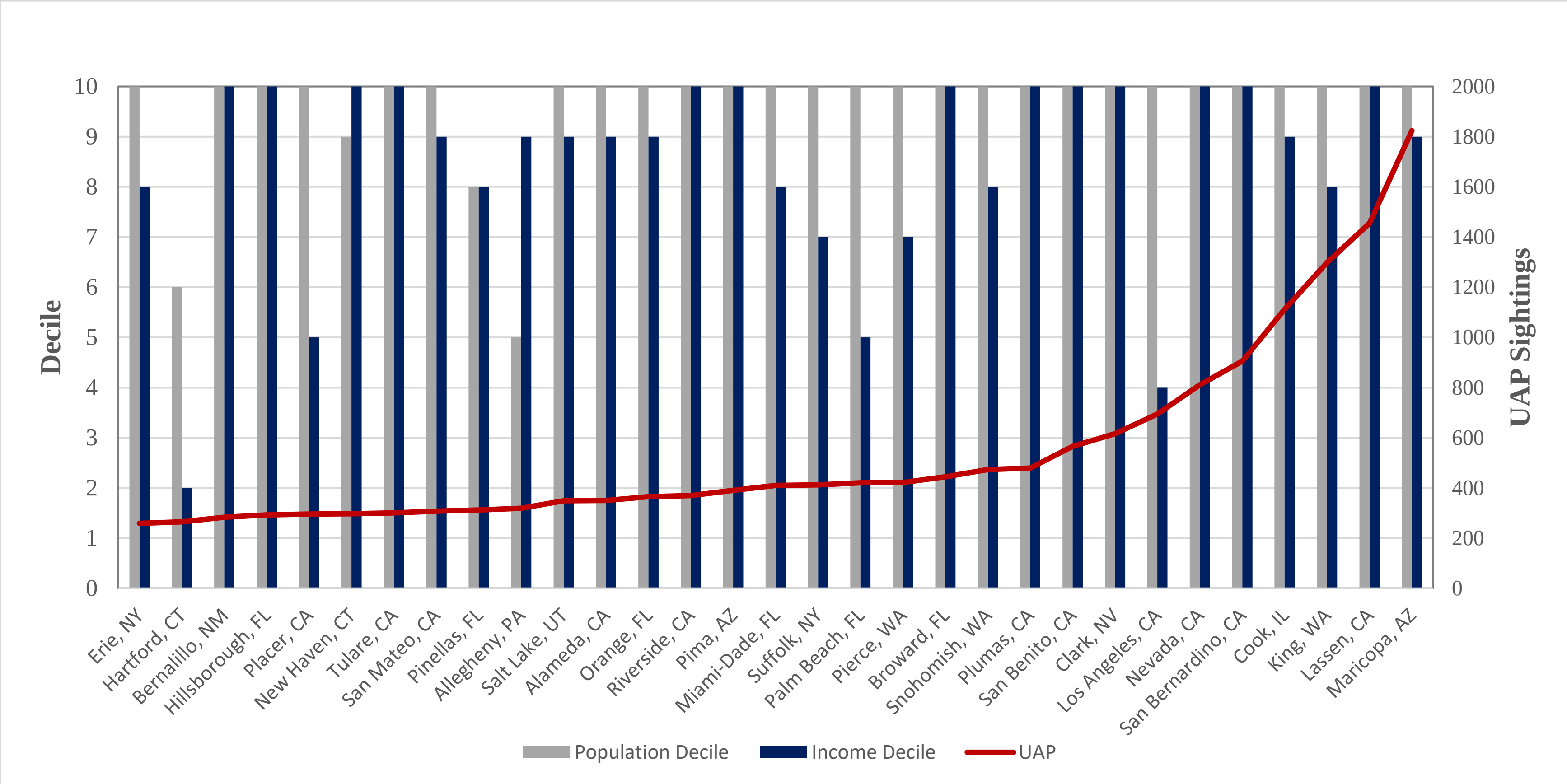
Notes: The figure plots the total number of UAP sightings at the U.S. national level by month, 2000-2020, based on the database of NUFORC. Shaded areas denote U.S. recessions, determined by the NBER.

Figure 2: UAP Sightings Across U.S. Counties, 2000-2017



Notes: The figure plots choropleth map of U.S. counties for the period of 2000-2017. The map indicates the total number of UAP sightings during the period, based on the database of NUFORC.

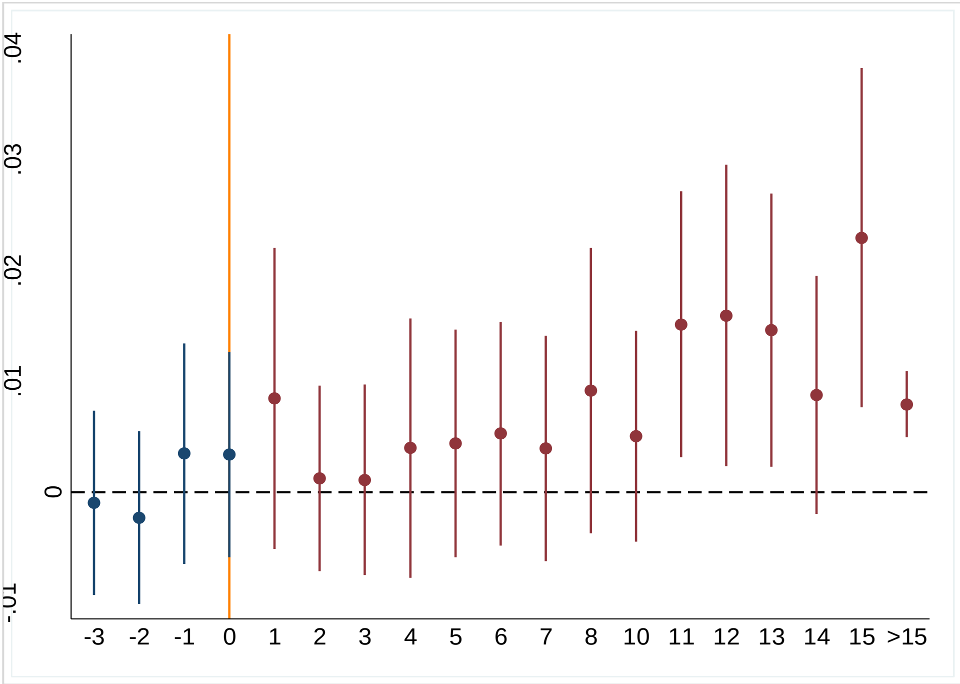
Figure 3: Top U.S. Counties by UAP Sightings



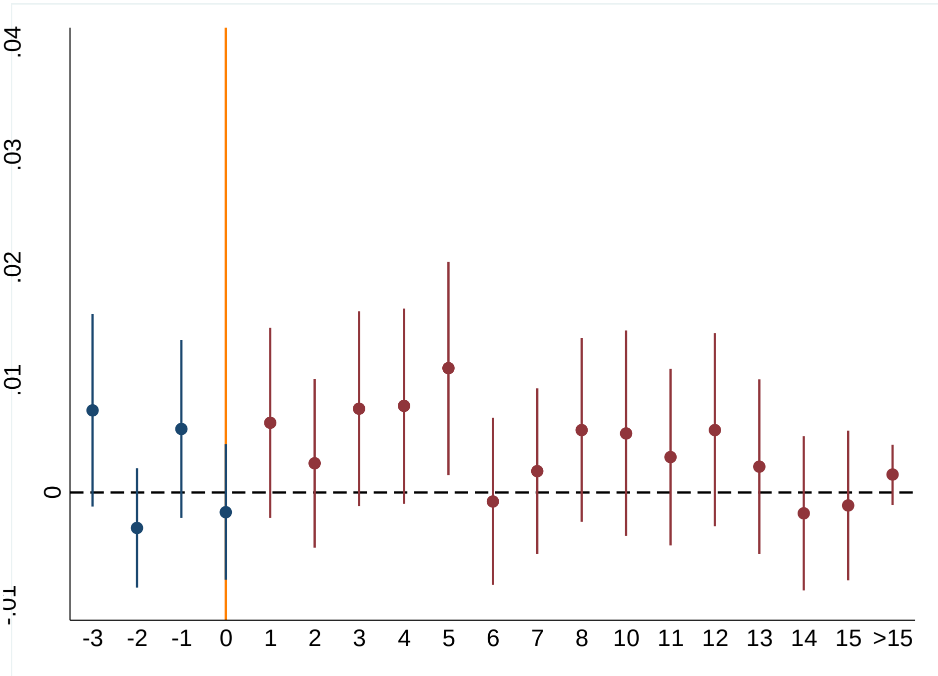
Notes: The figure plots deciles of annual income and population, in conjunction with total UAP sightings, for U.S. counties with the highest UAP sightings during the period 2000-2017 (top percentile). Income and population deciles are derived from the distribution of U.S. counties by their average annual income and population over the period, based on the U.S. BEA data. The number of UAP sightings is computed as the total number of sightings over the period, based on the NUFORC data.

Figure 4: Event Study of UAP sightings and Lockdowns

Panel A: Actual Data



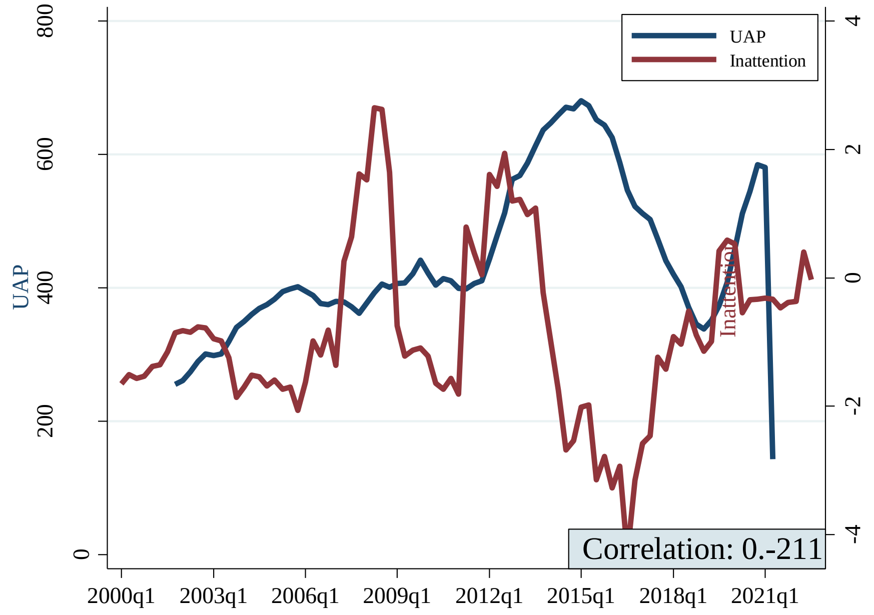
Panel B: Placebo Test



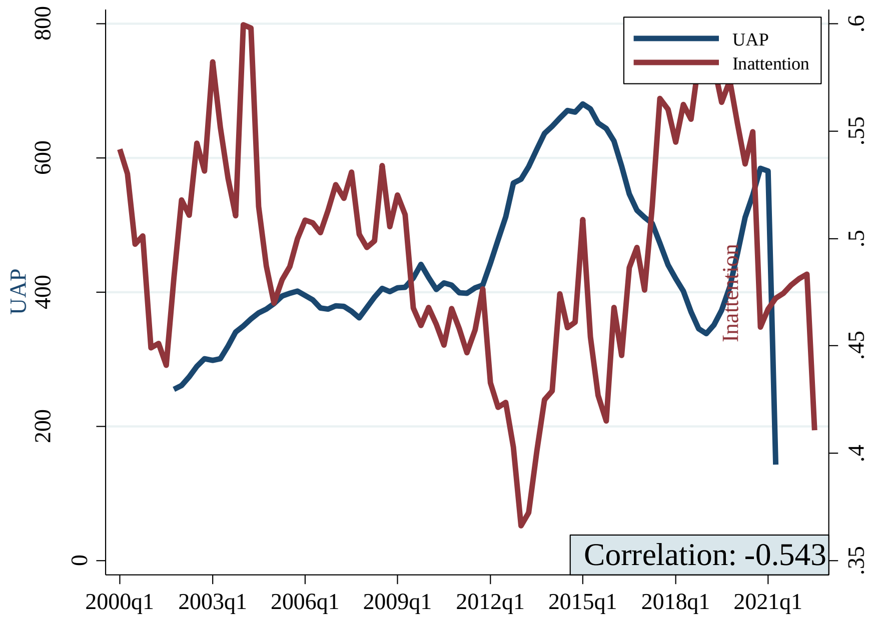
Notes: The figure plots coefficient estimates of γ^k in specification (3). The horizontal axis indicates k, the number of days before or after the start of a lockdown ($k = 0$). Panel A uses actual daily data for 2019-2020. Panel B is a placebo test, using 2019 data with lockdown dates from 2020. The dots show the point-estimates and the whiskers describes 90% confidence intervals, based on standard errors clustered at the county level.

Figure 5: UAP Sightings and Measures of Inattention

Panel A: Coibion and Gorodnichenko (2015)



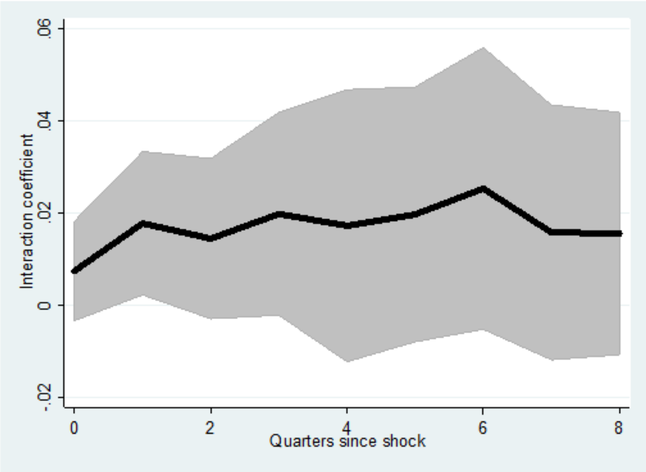
Panel B: Goldstein (2023)



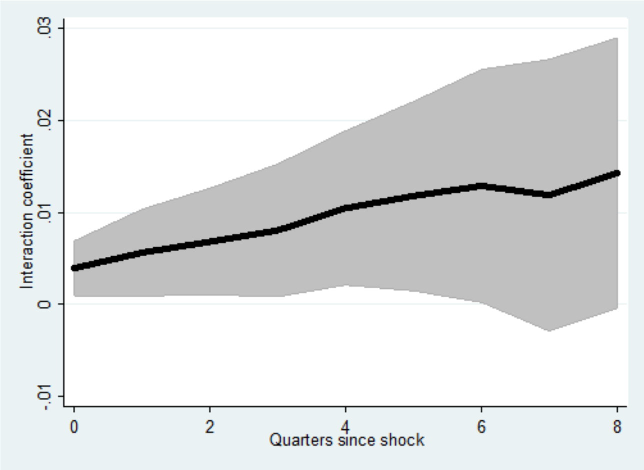
Notes: The figure compares the measure of UAP sightings over time with existing measures of inattentions. The red lines in panels A and B show coefficient estimates of specifications (7) and (8), respectively. The specifcations were estimated quarter by quarter, using SPF forecast data (with horizon $h = 3$) from the last eight quarters (and real-time data for the forecast errors in specification (7)). The forecast data includes all the variables in the SPF with avaialble realizations (excluding long-run forecasts). The UAP measure is a moving average of UAP sightings over the last eight quarters.Correlation between measures is reported in the boxes (signficant at 5% level).

Figure 6: Differential Impulse Response toMmonetary Shocks: U.S. States, Quarterly

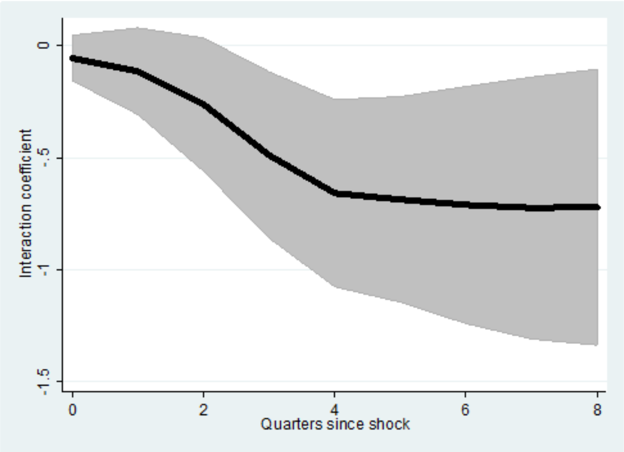
Panel A: GDP



Panel B: Employment



Panel C: Unemployment rate



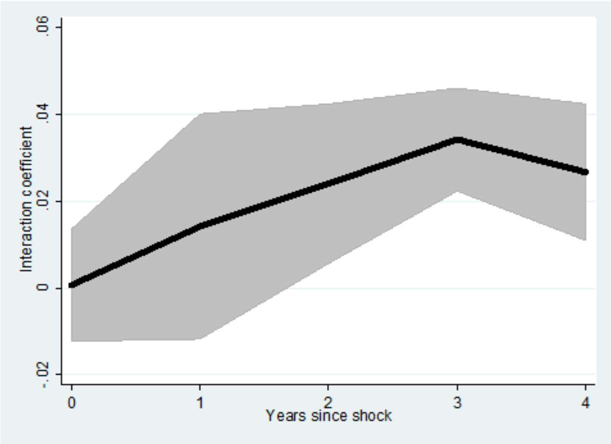
Notes: The figure discribes the dynamics of the interaction coefficient β_h from

$$y_{it+h} - y_{it} = \alpha_{ih} + \mu_{th} + \beta_h UAP_{it}\varepsilon_t^m + \sum_{k=0}^{3} \delta_k y_{it-k} + e_{ith}$$

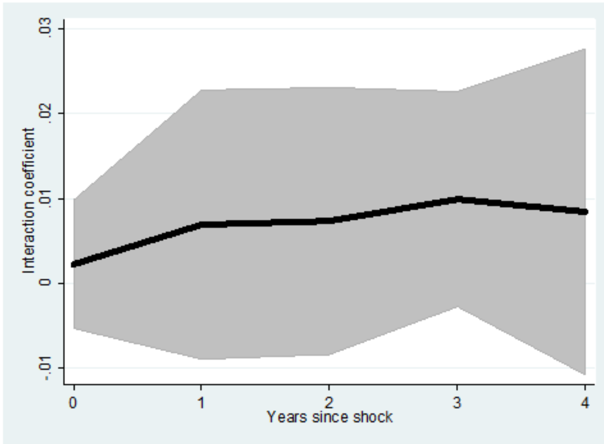
where y_{it} is the outcome variable in each panel (log of GDP per capita, log of employment per capita and unemployment rate), α_{ih} and μ_{th} are state and time effects, respectively, UAP_{it} is log of UAP sightings per capita and ε_t^m is the monetary shock. The sample period is 2000Q1-2017Q4 (quarterly). Shaded area denotes 90% confidence interval, based on double-clustered standard errors.

Figure 7: Differential Impulse Response to Monetary Shocks: U.S. States, Annual

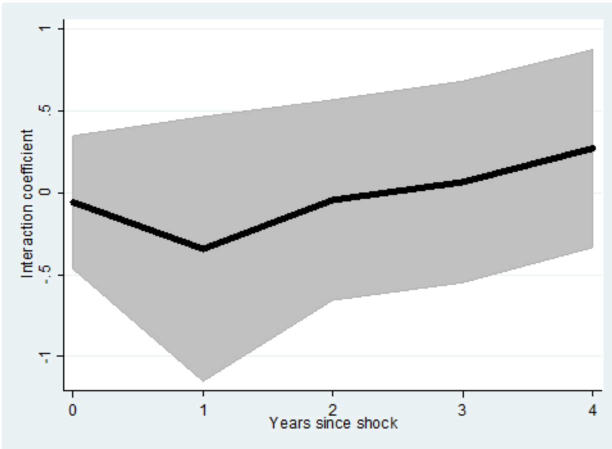
Panel A: GDP



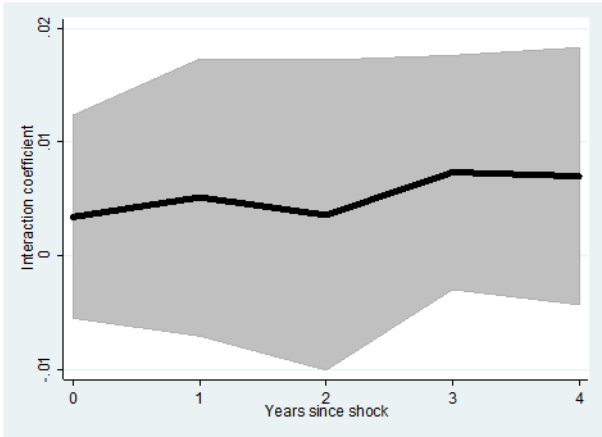
Panel B: Employment



Panel C: Unemployment rate



Panel D: Consumption



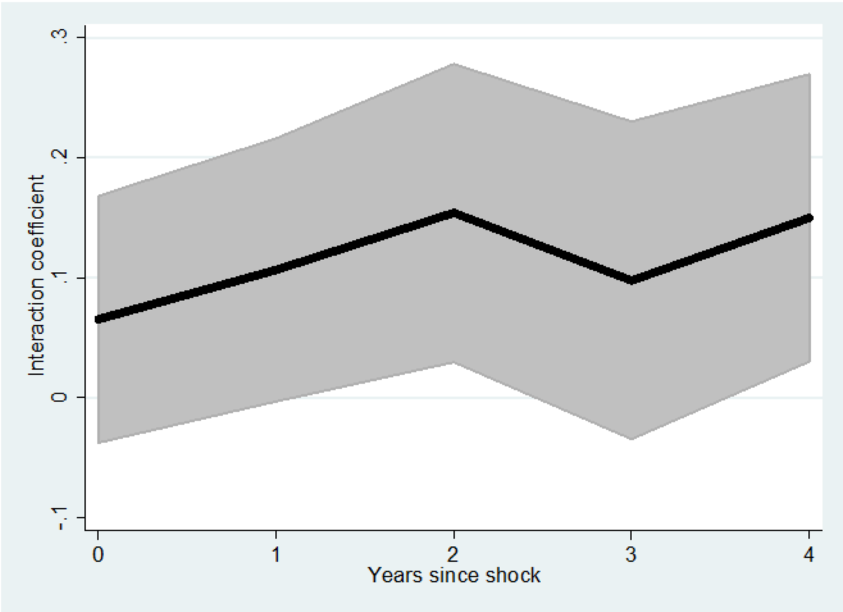
Notes: The figure discribes the dynamics of the interaction coefficient β_h from

$$y_{it+h} - y_{it} = \alpha_{ih} + \mu_{th} + \beta_h UAP_{it}\varepsilon_t^m + \delta y_{it} + e_{ith}$$

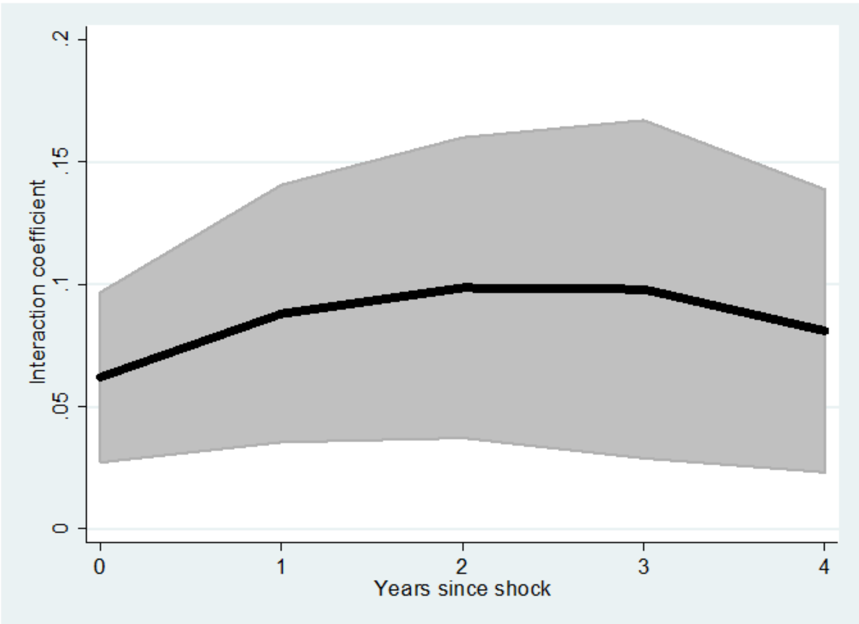
where y_{it} is the outcome variable in each panel (log of GDP per capita, log of employment per capita, unemployment rate and log of private consumption per capita), α_{ih} and μ_{th} are state and time effects, respectively, UAP_{it} is log of UAP sightings per capita and ε_t^m is the monetary shock. The sample period is 2000-2017 (annual). Shaded area denotes 90% confidence interval, based on double-clustered standard errors.

Figure 8: Differential Impulse Response to Monetary Shocks: U.S. Counties, Annual

Panel A: GDP



Panel B: Employment



Notes: The figure discribes the dynamics of the interaction coefficient β_h from

$$y_{it+h} - y_{it} = \alpha_{ih} + \mu_{th} + \beta_h UAP_{it}\varepsilon_t^m + \delta y_{it} + e_{ith}$$

where y_{it} is the outcome variable in each panel (log of GDP per capita, log of employment per capita, unemployment rate and log of privte consumtion per capita), α_{ih} and μ_{th} are county and time effects, respectively, UAP_{it} is log of UAP sightings per capita and ε_t^m is the monetary shock. The sample period is 2000-2017 (annual). Shaded area denotes 90% confidence interval, based on double-clustered standard errors.

TABLE 1
UAP Sighting and Income in U.S. Counties 2000-2017

	Between County			Within County		
	(1)	(2)	(3)	(4)	(5)	(6)
$income_{it}$	2.369***	1.854***		-1.953***		
	(0.364)	(0.304)		(0.457)		
$income_{it-1}$			0.275**		-2.177***	-1.408***
			(0.097)		(0.480)	(0.365)
UAP_{it-1}			0.793***			0.384***
			(0.041)			(0.076)
$county\ effect$	No	No	No	Yes	Yes	Yes
$year\ effect$	No	No	No	Yes	Yes	Yes
$population$	Yes	Yes	Yes	No	No	No
$density$	Yes	Yes	Yes	Yes	Yes	Yes
$weather$	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	46,540	46,540	43,926	46,524	43,907	43,907
R^2	0.193	0.195	0.707	0.726	0.739	0.778

Notes: The table reports coefficient estimates from U.S. county-level regressions, based on specification (1). The regressions apply annual data for the period of 2000-2017. Column (1) reports results from cross-sectional regression of the period means, with robust standard errors in parentheses. The results in the other columns are from panel regressions with double clustered standard errors at county and year level. ***, **, * denote significance at 0.01, 0.05, and 0.10 levels.

TABLE 2
UAP Sighting and Income in U.S States 2000Q1-2017Q4

	Between County			Within County		
	(1)	(2)	(3)	(4)	(5)	(6)
$income_{it}$	26.643	25.903***		-45.640***		
	(21.425)	(7.036)		(16.140)		
$income_{it-1}$			6.852***		-46.830***	-32.087***
			(2.212)		(16.502)	(10.667)
UAP_{it-1}			0.736***			0.325***
			(0.041)			(0.070)
$county\ effect$	No	No	No	Yes	Yes	Yes
$quarter\ effect$	No	No	No	Yes	Yes	Yes
$calendar\ quarter$	No	Yes	Yes	No	No	No
$population$	Yes	Yes	Yes	No	No	No
$density$	Yes	Yes	Yes	Yes	Yes	Yes
$weather$	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	3,456	3,456	3,408	3,456	3,408	3,408
R^2	0.353	0.533	0.794	0.845	0.846	0.863

Notes: The table reports coefficient estimates from U.S. state-level regressions, based on specification (1). The regressions apply quarterly data for the period of 2000Q1-2017Q4. Column (1) reports results from cross-sectional regression of the period means with robust standard errors in parentheses. The results in the other columns are from panel regressions with double clustered standard errors at state and quarter level. ***, **, * denote significance at 0.01, 0.05, and 0.10 levels.

TABLE 3
UAP Sighting and Business Cycle in the U.S.: 2000M1-2021M4

	(1)	(2)	(3)	(4)	(5)
$income_t$	-2.136**			-1.980**	
	(1.038)			(0.916)	
$unemployment_t$		3.717**			
		(1.743)			
$Consumer\ Confidence_t$			-4.521**		
			(2.002)		
$income_{t-1}$					-1.182***
					(0.412)
UAP_{t-1}					0.668***
					(0.078)
$Population$	7.909***	3.686***	3.850***	7.595***	3.554***
	(1.851)	(0.676)	(0.670)	(1.797)	(0.941)
$Google\ Trends$				0.226**	0.098**
$(from\ 2004)$				(0.103)	(0.051)
Obs.	255	255	253	207	207
R^2	0.354	0.352	0.371	0.184	0.561

Notes: The table reports coefficient estimates from time-series regressions for the U.S, based on specification (1). The regressions apply monthly data for the period of 2000M1-2021M4. HAC standard errors are in parentheses. ***, **, * denote significance at 0.01, 0.05, and 0.10 levels.

TABLE 4
UAP Sightings in U.S. Counties: The Effect of COVID Lockdowns

	(1)	(2)	(3)	(4)	(5)
$order\ 6-7$	-0.005	-0.008***	-0.007***	-0.007***	-0.006***
	(0.004)	(0.002)	(0.001)	(0.002)	(0.002)
$order\ 3-5$	-0.010***	-0.011***		-0.010***	-0.007***
	(0.002)	(0.001)		(0.001)	(0.001)
GT_{t-1}					0.006***
					(0.001)
$county\ effect$	No	Yes	Yes	Yes	Yes
$calendar\ week\ effect$	No	No	Yes	Yes	Yes
$day\ of\ week\ effect$	No	No	Yes	Yes	Yes
Obs.	613,930	613,930	613,930	613,930	613,930
R^2	0.0003	0.051	0.051	0.051	0.051

Notes: The table reports coefficient estimates from US county-level regressions based on specification (2), using daily data for 2019-2020. The dependent variable is the number of UAP sightings. Order 6-7 and order 3-5 are dummy variables, taking the value of 1 according to CDC COVID order category. Standard errors in parentheses are clustered at the county level. ***, **, * denote significance at 0.01, 0.05, and 0.10 levels.

TABLE 5
UAP Sightings and inattention to macroeconomic variables

Variable	Correlation	Variable	Correlation
1. Corporate bond yield	0.091	10. Real exports	-0.130
2. CPI inflation	**0.272**	11. Federal consumption and investment	**0.214**
3. Corporate profits	-0.159	12. Real GDP	**-0.383**
4. Housing starts	0.184	13. Nonresidential investment	0.161
5. Industrial production	0.023	14. Residential investment	0.157
6. Nominal GDP	**-0.684**	15. State and local consumption and investment	**0.574**
7. GDP deflator	-0.076	16. 3-month Treasury bill rate	-0.110
8. Private inventories	**-0.196**	17. 10-year Treasury bond rate	**-0.223**
9. Real consumption	**0.332**	18. Unemployment	0.088

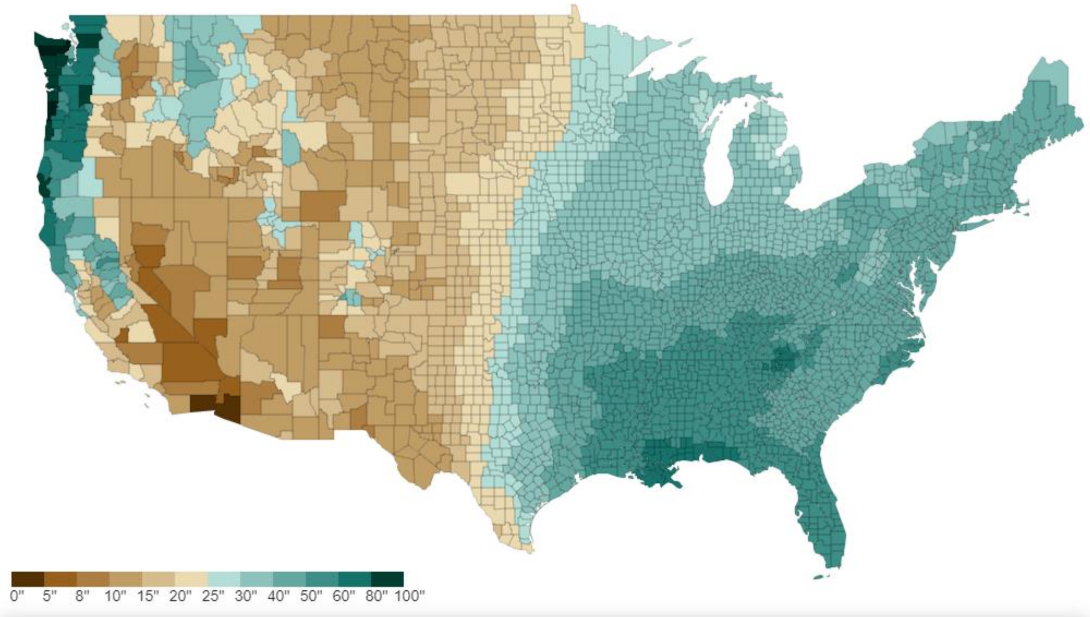
Notes: The table reports the time correlation of UAP sightings with inattention to various variables in the SPF survey. For each variable, specifcation (8) is estimated quarter by quarter, using SPF forecast data (with horizon $h = 3$) from the last eight quarters. The UAP measure is a moving average of UAP sightings over the last eight quarters. The table reports the correlation of the UAP time-series with the time-series of inattention estimates of each macroeconomic variable. Bold correlation values are significant at the 5% level.

ONLINE APPENDIX

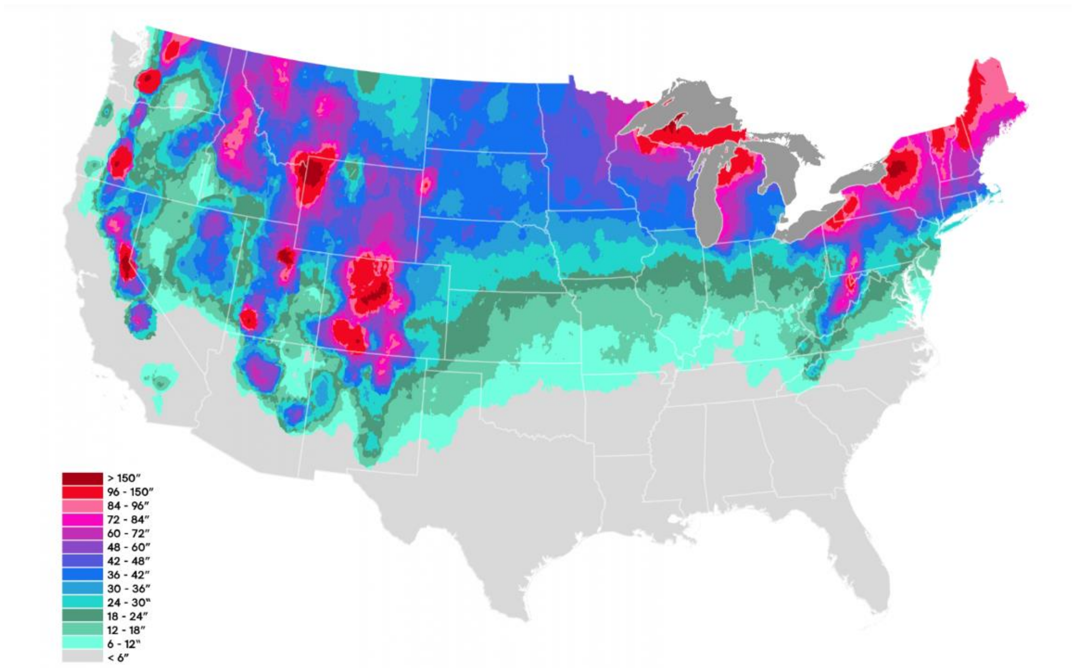
Appendix A: Additional figures and tables

Figure A.1: Percipitation and Snowfall Across U.S. Counties

Panel A: Percipitation



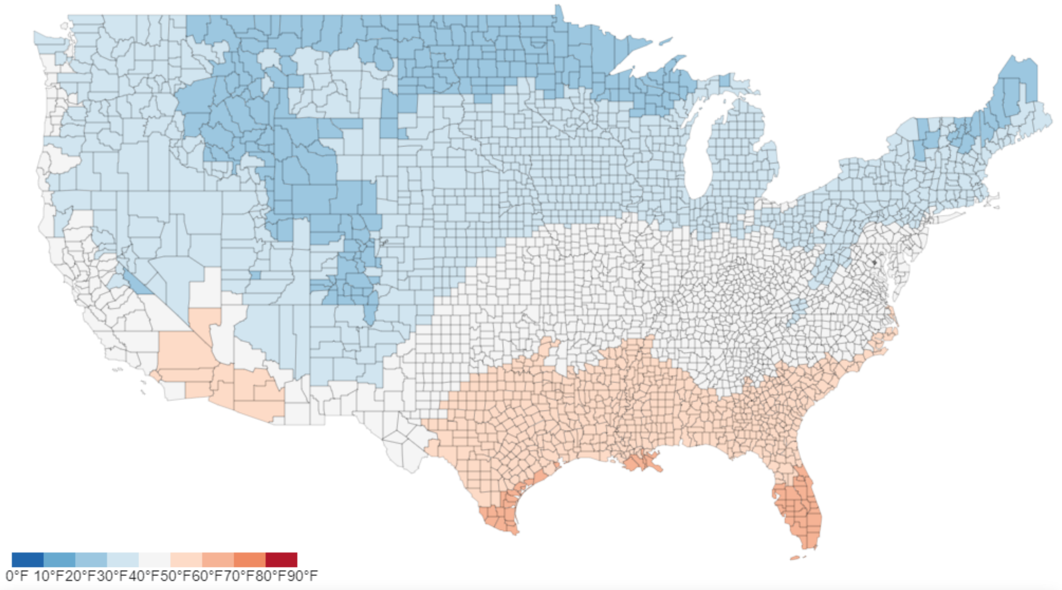
Panel B: Snowfall



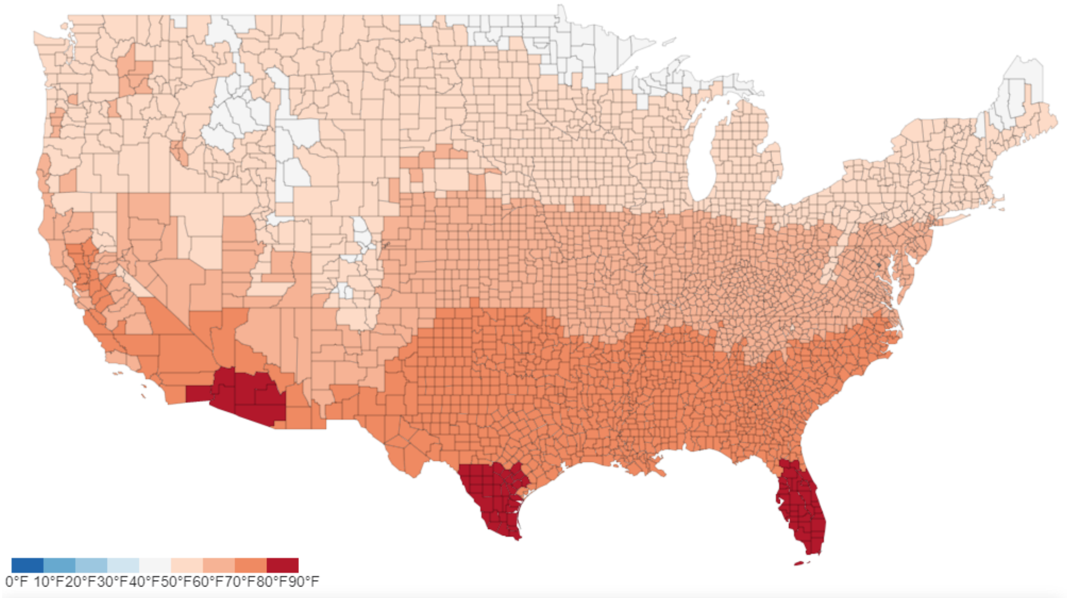
Notes: The figure plots a choropleth map of the average multi-annual percipitation across U.S. counties (in mm). Source: National Oceanic and Atmospheric Administration.

Figure A.2: Tempratures Across U.S. Counties

Panel A: Minimum Temprature



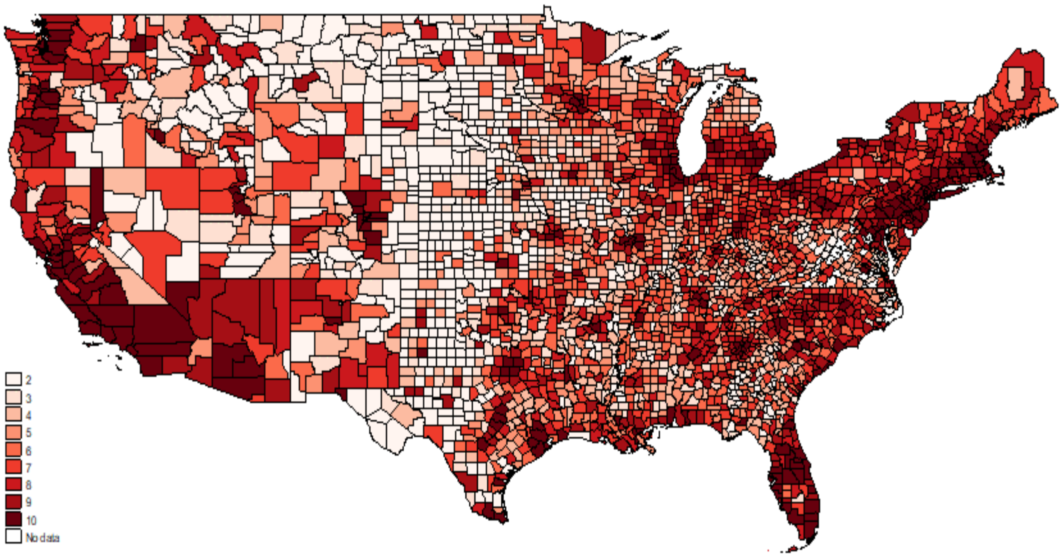
Panel B: Maximum Temprature



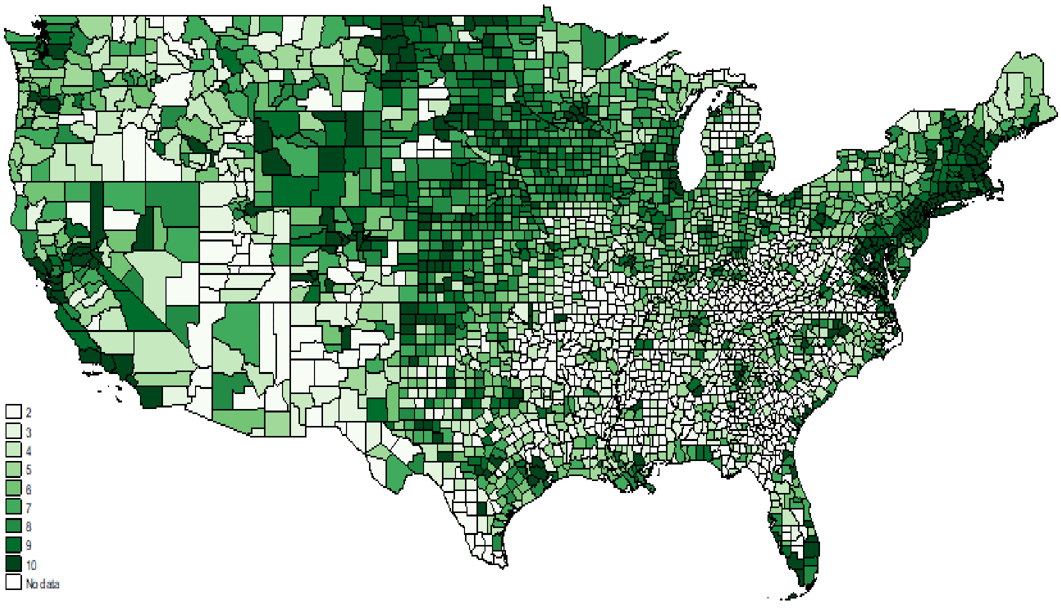
Notes: The figure plots a choropleth map of the average multi-annual tempratures across U.S. counties (in Fahrenheit). Source: National Oceanic and Atmospheric Administration.

Figure A.3: Population and Income Across U.S. Counties, 2000-2017

Panel A: Population

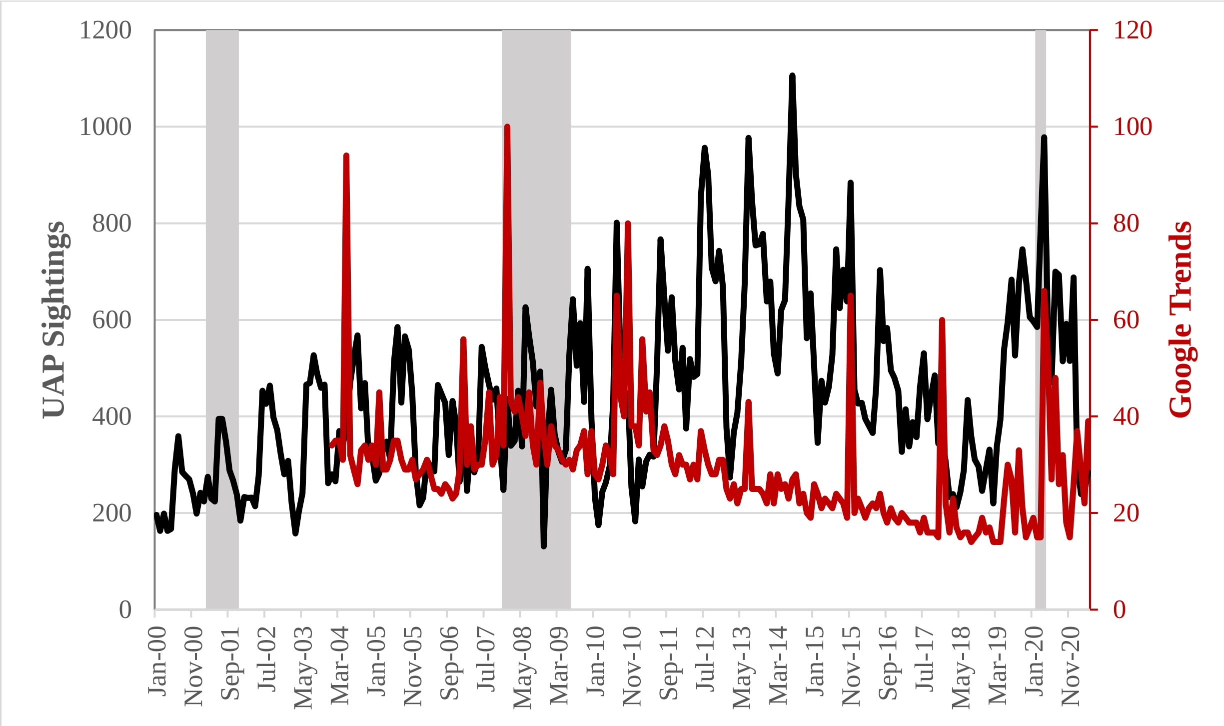


Panel B: Income



Notes The figure plots choropleth maps of population and income across U.S. counties for the period of 2000-2017. Panel A shows deciles of the mean annual population over the period. Panel B shows deciles of the mean annual personal income over the period. Data source: U.S. Bureau of Economic Analysis.

Figure A.4: Reported UAP Sightings and Google Searches

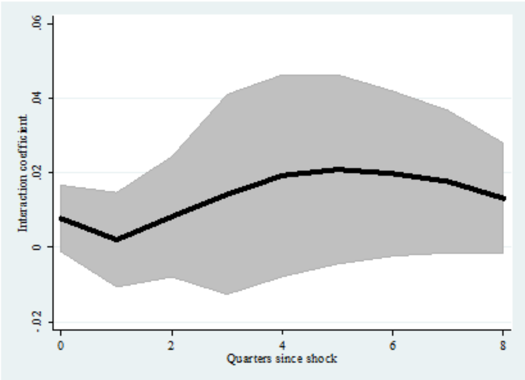


Notes: The black line plots the total number of UAP sightings at the U.S. national level by month, 2000-2020, based on the database of NUFORC. The red line plots Google search index for the word "UFO" in the U.S., based on Google Trends data. Shaded areas denote U.S. recessions, determined by the NBER.

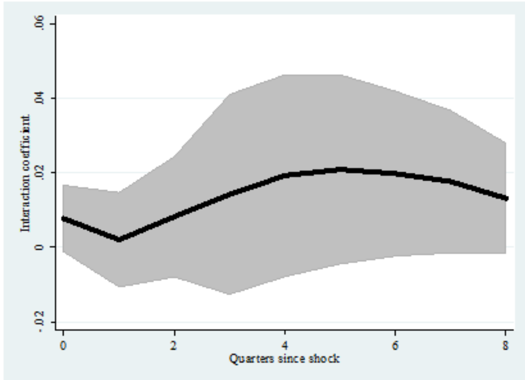
Figure A.5: Differential Impulse Response to Monetary Shocks in Jarocinski and Karadi (2020)

Panel A: GDP

Principal Component

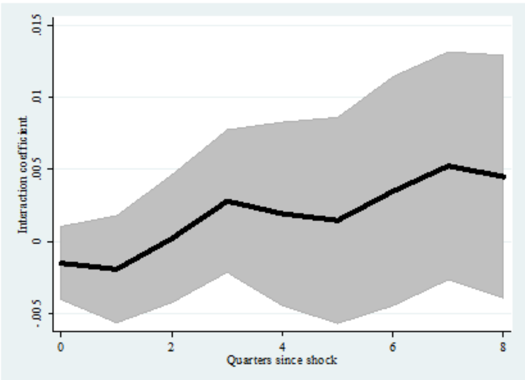


Excluding Information Shocks

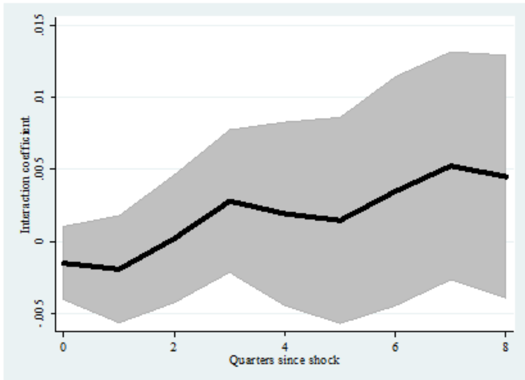


Panel B: Employment

Principal Component

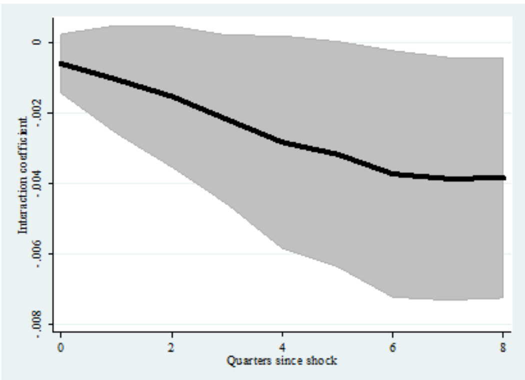


Excluding Information Shocks

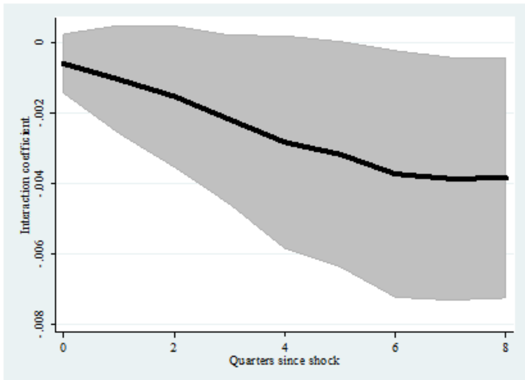


Panel C: Unemployment rate

Principal Component



Excluding Information Shocks



Notes: The figure discribes the dynamics of the interaction coefficient β_h from

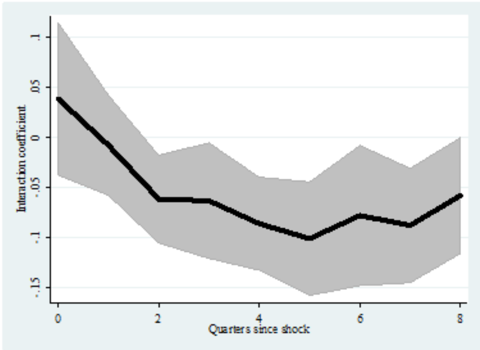
$$y_{it+h} - y_{it} = \alpha_{ih} + \mu_{th} + \beta_h UAP_{it}\varepsilon_t^m + \sum_{k=0}^{3} \delta_k y_{it-k} + e_{ith}$$

where y_{it} is the outcome variable in each panel (log of GDP per capita, log of employment per capita and unemployment rate), α_{ih} and μ_{th} are state and time effects, respectively, UAP_{it} is log of UAP sightings per capita. In the left figures ε_t^m applies the monetary shocks from Jarocinski and Karadi (2020) based on the principal component of five interest rates. In the right figures ε_t^m applies the monetary shocks after excluding the information effect, based on the decomposition in Jarocinski and Karadi (2020). The sample period 2000Q1-2017Q4 (quarterly). Shaded area denotes 90% confidence interval, based on double-clustered standard errors.

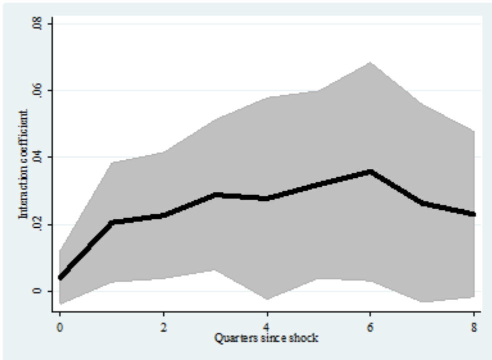
Figure A.6: Differential Impulse Response to Monetary Shocks - Assymetry (U.S. states)

Panel A: GDP

Contractionary Shock

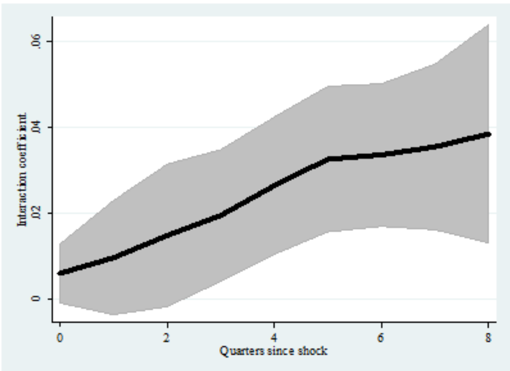


Expansionary Shock

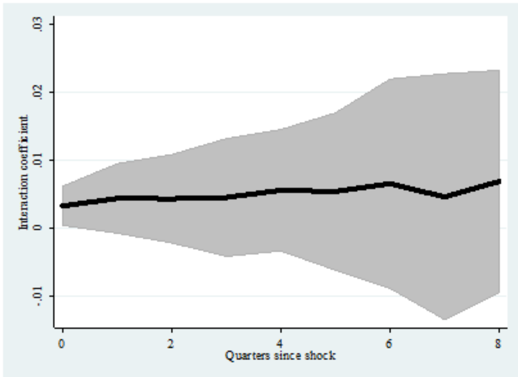


Panel B: Employment

Contractionary Shock

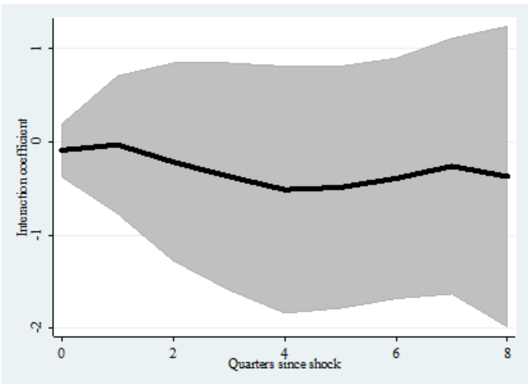


Expansionary Shock

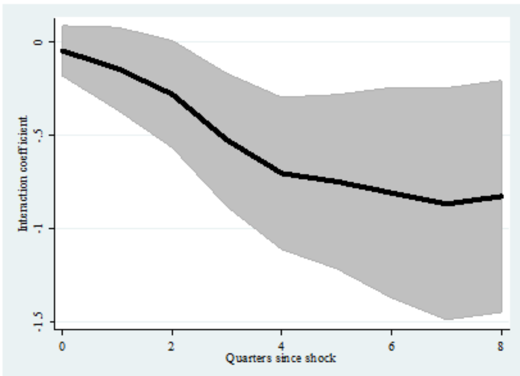


Panel C: Unemployment rate

Contractionary Shock



Expansionary Shock



Notes: The figure discribes the dynamics of the interaction coefficients β_h^p (left figures) and β_h^n (right figures) from

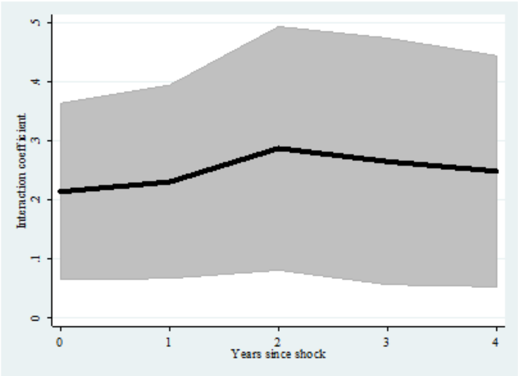
$$y_{it+h} - y_{it} = \alpha_{ih} + \mu_{th} + \beta_h^p UAP_{it}\varepsilon_t^m D_t^p + \beta_h^n UAP_{it}\varepsilon_t^m D_t^n + \sum_{k=0}^{3} \delta_k y_{it-k} + e_{ith}$$

where y_{it} is the outcome variable in each panel (log of GDP per capita, log of employment per capita and unemployment rate), α_{ih} and μ_{th} are state and time effects, respectively, UAP_{it} is log of UAP sightings per capita and ε_t^m is the monetary shock. The dummy variables D_t^p distinguish between positive (contractionary) and negative (expansionary) shocks. The sample period 2000Q1-2017Q4 (quarterly). Shaded area denotes 90% confidence interval, based on double-clustered standard errors.

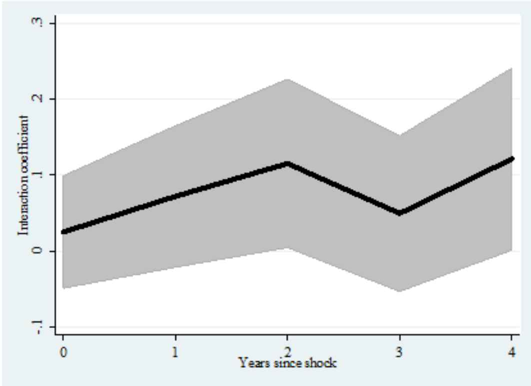
Figure A.7: Differential Impulse Response to Monetary Shocks - Assymetry (U.S. counties)

Panel A: GDP

Contractionary Shock

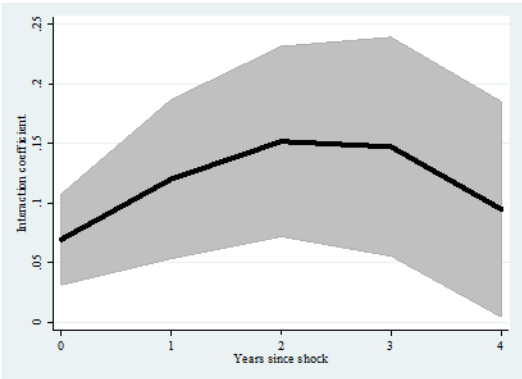


Expansionary Shock

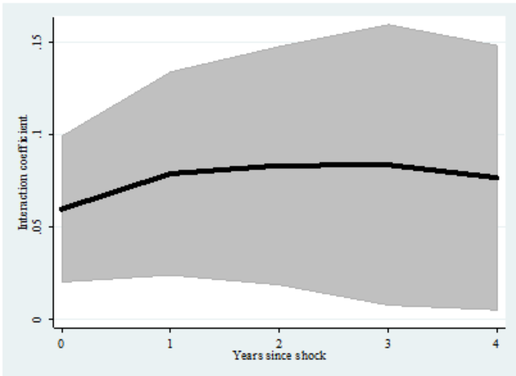


Panel B: Employment

Contractionary Shock



Expansionary Shock



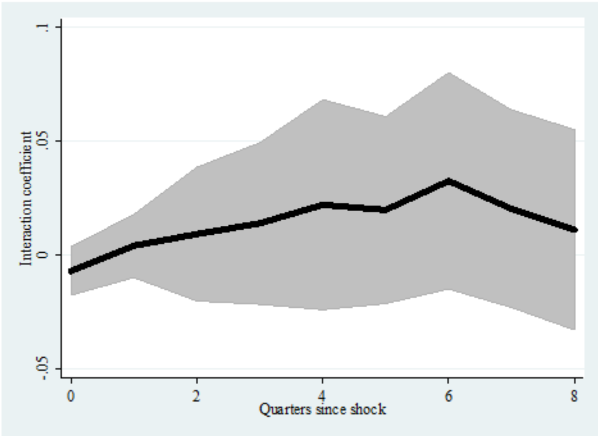
Notes: The figure discribes the dynamics of the interaction coefficients β_h^p (left figures) and β_h^n (right figures) from

$$y_{it+h} - y_{it} = \alpha_{ih} + \mu_{th} + \beta_h^p UAP_{it} \varepsilon_t^m D_t^p + \beta_h^n UAP_{it} \varepsilon_t^m D_t^n + \sum_{k=0}^{3} \delta_k y_{it-k} + e_{ith}$$

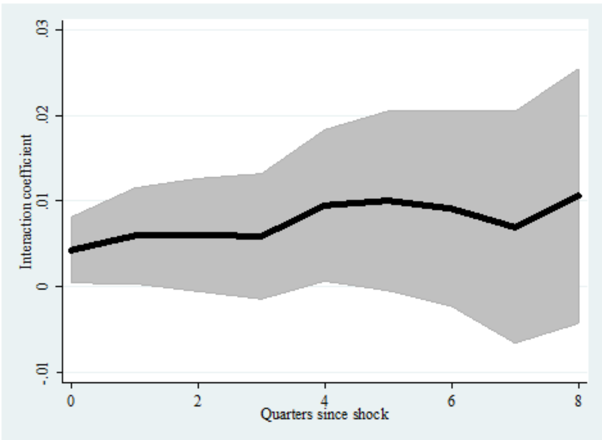
where y_{it} is the outcome variable in each panel (log of GDP per capita, log of employment per capita and unemployment rate), α_{ih} and μ_{th} are county and time effects, respectively, UAP_{it} is log of UAP sightings per capita and ε_t^m is the monetary shock. The dummy variables D_t^p distinguish between positive (contractionary) and negative (expansionary) shocks. The sample period 2000-2017 (annual). Shaded area denotes 90% confidence interval, based on double-clustered standard errors.

Figure A.8: Differential Impulse Response to Monetary Shocks: U.S. States, Quarterly (excluding 2008Q3-2009Q2)

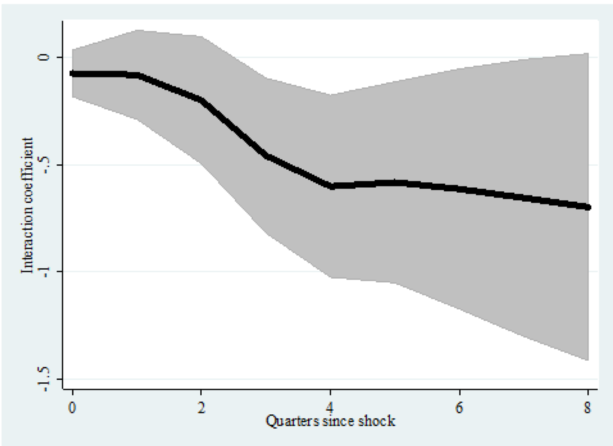
Panel A: GDP



Panel B: Employment



Panel C: Unemployment rate



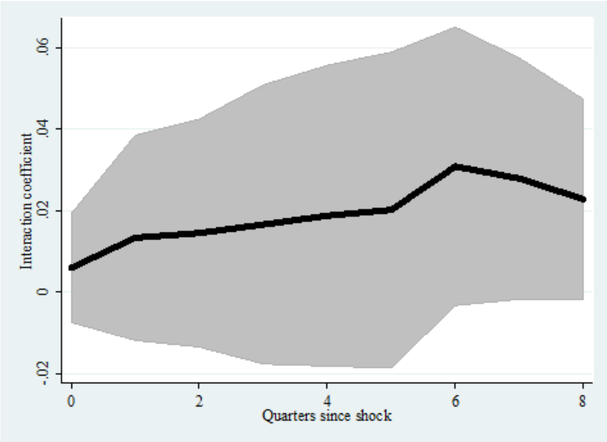
Notes: The figure discribes the dynamics of the interaction coefficient β_h from

$$y_{it+h} - y_{it} = \alpha_{ih} + \mu_{th} + \beta_h UAP_{it}\varepsilon_t^m + \sum_{k=0}^{3} \delta_k y_{it-k} + e_{ith}$$

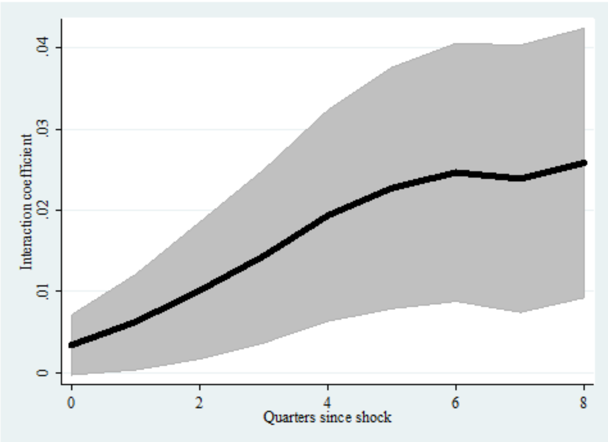
where y_{it} is the outcome variable in each panel (log of GDP per capita, log of employment per capita and unemployment rate), α_{ih} and μ_{th} are state and time effects, respectively, UFO_{it} is log of UAP sightings per capita and ε_t^m is the monetary shock. The sample period is 2000Q1-2017Q4, excluding the quarters of 2008Q3-2009Q2. Shaded area denotes 90% confidence interval, based on double-clustered standard errors.

Figure A.9: Differential Impulse Response to Monetary Shocks: U.S. States, Quarterly (macro lags)

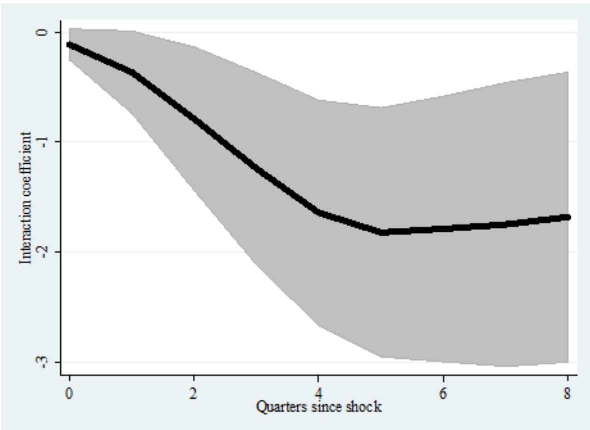
Panel A: GDP



Panel B: Employment



Panel C: Unemployment rate



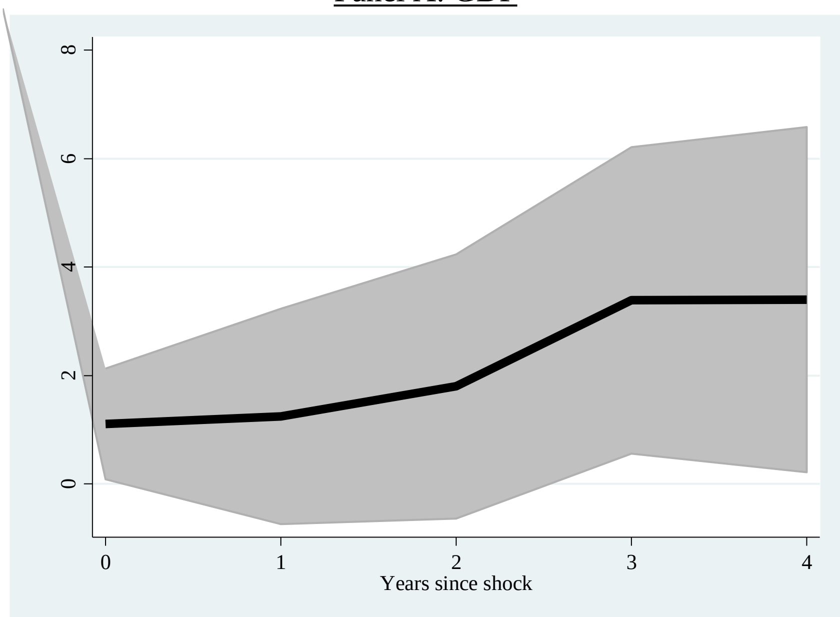
Notes: The figure discribes the dynamics of the interaction coefficient β_h from

$$y_{it+h} - y_{it} = \alpha_{ih} + \mu_{th} + \beta_h UAP_{it} \varepsilon_t^m + + \sum_{k=0}^{3} \delta_k y_{it-k} + \sum_{k=0}^{3} \boldsymbol{\theta}_k \boldsymbol{X}_{t-k} + e_{ith}$$

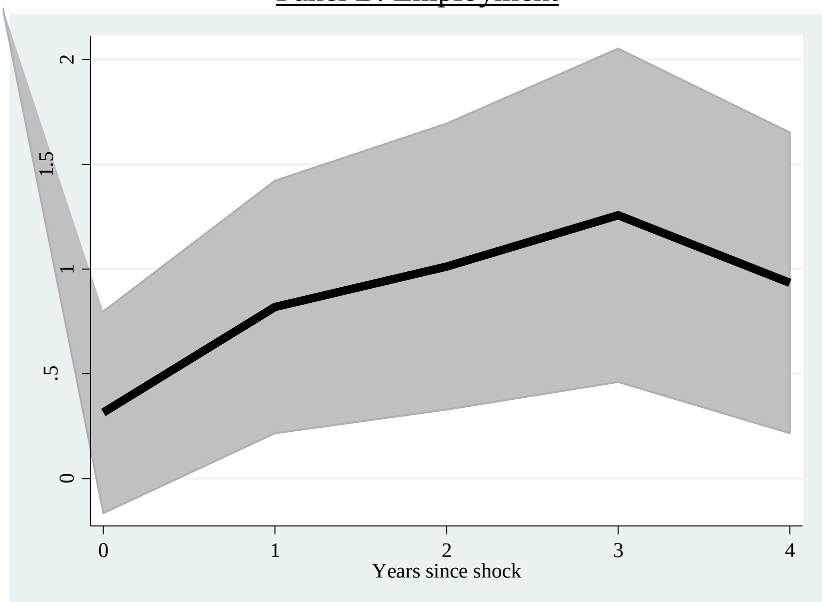
where y_{it} is the outcome variable in each panel (log of GDP per capita, log of employment per capita and unemployment rate), α_{ih} is a state effect, respectively, UAO_{it} is log of UAP sightings per capita, ε_t^m is the monetary shock, $\boldsymbol{X}_{t-k}$ is a set of U.S. macro variables, including inflation rate, GDP growth and unemployment rate. The sample period 2000Q1-2017Q4 (quarterly). Shaded area denotes 90% confidence interval, based on double-clustered standard errors.

Figure A.10: Differential Impulse Response to Monetary Shocks: U.S. Counties, Annual – IV Approach

Panel A: GDP



Panel B: Employment



Notes: The figure discribes the dynamics of the interaction coefficient β_h from estimating

$$y_{it+h} - y_{it} = \alpha_{ih} + \mu_{th} + \beta_h \widehat{UAP}_{it} \varepsilon_t^m + \delta y_{it} + e_{ith}$$

by IV approach. y_{it} is the outcome variable in each panel (log of GDP per capita, log of employment per capita, unemployment rate and log of privte consumtion per capita), α_{ih} and μ_{th} are county and time effects, respectively, $\widehat{UAP}_{it}$ is the standardized residual from regressing UAP sightings on population, density and weather variables. ε_t^m is the monetary shock. The interaction $\widehat{UAP}_{it}\varepsilon_t^m$ is instrumented by the interaction $oil_{it}\varepsilon_t^m$ and by oil_{it}, where oil_{it} is an indicator for a county lying above a booming shale formation multiplied by the annual log change in oil price. The sample period is 2000-2017 (annual). Shaded area denotes 90% confidence interval, based on double-clustered standard errors.

TABLE A.1
Summary Statistics for the Panel of U.S. Counties, 2000-2017

Variable	Obs.	Mean	Std. Dev.
UAP sightings:	54,337	1.30	4.89
Sociodemographic:			
Personal Income Per Capita (Thousand Dollars)	53,265	32.99	10.78
GDP ((K$ Per Capita)	50,307	48.41	325.03
Employment	53,265	57,326	200,452
Population	53,265	98,567	318,751
Area (Square Miles)	54,319	1,207	4,022
Weather:			
Precipitation (Inches)	51,800	34.53	15.75
Snow (Inches)	51,071	18.07	24.97
Max. Temperature (Fahrenheit)	47,872	65.99	9.56
Min. Temperature (Fahrenheit)	47,873	43.48	11.71

Notes: The table reports summary statistics for the panel of U.S. counties, based on annual data for the period of 2000-2017. Data sources: NUFORC (UAP sightings); U.S. Bureau of Economic Analysis (sociodemographic data); National Oceanic and Atmospheric Administration (weather).

TABLE A.2

UAP Sighting and Income in U.S. Counties: Robustness to Income Levels and Poverty Rates

	Income		Income		Poverty rate	
	Below U.S. level	Above U.S. level	Below av. county	Above av. county	Below av. county	Above av. county
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Between county						
$income_i$	1.497**	3.323***	1.033**	3.792***	1.996***	1.447***
	(0.597)	(0.154)	(0.500)	(0.571)	(0.567)	(0.482)
$county\ effect$	No	No	No	No	No	No
$year\ effect$	No	No	No	No	No	No
$population$	Yes	Yes	Yes	Yes	Yes	Yes
$density$	Yes	Yes	Yes	Yes	Yes	Yes
$weather$	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	40,320	6,220	24,456	22,084	26,443	20,097
R^2	0.156	0.216	0.101	0.220	0.201	0.713
Panel B: Within county						
$income_{it-1}$	-1.168***	-2.539***	-0.497*	-2.414***	-2.097***	-0.530**
	(0.337)	(0.731)	(0.279)	(0.699)	(0.517)	(0.210)
ufo_{it-1}	0.313***	0.325***	0.293***	0.400***	0.358***	0.420***
	(0.067)	(0.083)	(0.061)	(0.079)	(0.056)	(0.102)
$county\ effect$	Yes	Yes	Yes	Yes	Yes	Yes
$year\ effect$	Yes	Yes	Yes	Yes	Yes	Yes
$population$	Yes	Yes	Yes	Yes	Yes	Yes
$density$	Yes	Yes	Yes	Yes	Yes	Yes
$weather$	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	37,933	5,898	22,992	20,743	24,972	18,884
R^2	0.799	0.767	0.758	0.784	0.799	0.713

Notes: The table reports coefficient estimates from U.S. county-level regressions, based on specification (1). The regressions apply annual data for the period of 2000-2017, split to two groups. In columns (1) and (2), the sample is split according to U.S.-level annual personal income. In columns (3) and (4), the sample is split according to average annual personal income across counties. In columns (5) and (6), the sample is split according to the average poverty rate across counties in 2020. Panel A reports results from cross-sectional regression of the period means, with robust standard errors in parentheses. Panel B reports results from panel regressions with double clustered standard errors at county and year level in parentheses. ***, **, * denote significance at 0.01, 0.05, and 0.10 levels.

TABLE A.3
UAP Sighting and Income in U.S. Counties: Robustness to Additional Sample Splitting

	UAP		Population		Period	
	Below av. county	Above av. county	Below av. county	Above av. county	Before 2010	Since 2010
	(1)	(2)	(3)	(1)	(2)	(3)
Panel A: Between county						
$income_i$	0.166**	2.339***	0.763***	0.788	1.869***	2.755***
	(0.019)	(0.513)	(0.253)	(1.360)	(0.364)	(0.412)
$county\ effect$	No	No	No	No	No	No
$year\ effect$	No	No	No	No	No	No
$population$	Yes	Yes	Yes	Yes	Yes	Yes
$density$	Yes	Yes	Yes	Yes	Yes	Yes
$weather$	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	35,535	11,005	37,339	9,208	26,269	20,271
R^2	0.115	0.194	0.029	0.278	0.168	0.222
Panel B: Within county						
$income_{it-1}$	-0.231***	-5.487**	-0.264**	-5.447**	-0.197	-2.151***
	(0.063)	(1.995)	(0.095)	(1.782)	(0.242)	(0.616)
ufo_{it-1}	0.007	0.387***	0.197	0.430***	0.230	0.210**
	(0.005)	(0.075)	(0.124)	(0.066)	(0.130)	(0.081)
$county\ effect$	Yes	Yes	Yes	Yes	Yes	Yes
$year\ effect$	Yes	Yes	Yes	Yes	Yes	Yes
$population$	No	No	No	No	No	No
$density$	Yes	Yes	Yes	Yes	Yes	Yes
$weather$	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	33,568	9,750	35,199	8,701	23,638	20,228
R^2	0.295	0.801	0.693	0.778	0.755	0.841

Notes: The table reports coefficient estimates from U.S. county-level regressions, based on specification (1). The regressions apply annual data for the period of 2000-2017, split to two groups. In columns (1) and (2), the sample is split according to average annual number of UAP sightings across counties. In columns (3) and (4), the sample is split according to average annual population across counties. In columns (5) and (6), the sample is split between time periods. Panel A reports results from cross-sectional regression of the period means, with robust standard errors in parentheses. Panel B reports results from panel regressions with double clustered standard errors at county and year level in parentheses. ***, **, * denote significance at 0.01, 0.05, and 0.10 levels.

TABLE A.4
UAP Sighting and Income in U.S. Counties: Robustness to Additional Economic Variables

	Between County			Within County		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Employment						
$employment_{it}$	0.622**	0.662**		-0.519		
	(0.278)	(0.298)		(0.387)		
$employment_{it-1}$			0.130*		-0.993**	-0.721**
			(0.064)		(0.437)	(0.312)
UAP_{it-1}			0.795***			0.386***
			(0.041)			(0.076)
$county\ effect$	No	No	No	Yes	Yes	Yes
$year\ effect$	No	No	No	Yes	Yes	Yes
$population$	Yes	Yes	Yes	No	No	No
$density$	Yes	Yes	Yes	Yes	Yes	Yes
$weather$	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	46,540	46,540	43,926	46,524	43,907	43,907
R^2	0.186	0.188	0.707	0.725	0.738	0.778
Panel B: GDP						
GDP_{it}	0.532***	0.662**		-0.391***		
	(0.153)	(0.298)		(0.120)		
GDP_{it-1}			0.106**		-0.447***	-0.294***
			(0.039)		(0.124)	(0.097)
UAP_{it-1}			0.790***			0.340***
			(0.047)			(0.077)
$county\ effect$	No	No	No	Yes	Yes	Yes
$year\ effect$	No	No	No	Yes	Yes	Yes
$population$	Yes	Yes	Yes	No	No	No
$density$	Yes	Yes	Yes	Yes	Yes	Yes
$weather$	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	43,934	43,934	41,299	43,915	41,278	41,278
R^2	0.191	0.192	0.704	0.738	0.754	0.784

Notes: The table reports coefficient estimates from U.S. county-level regressions, based on specification (1). The regressions apply annual data for the period of 2000-2017. In Panel A, the economic variable ($ECON$) is the county-level employment per capita and in Panel B the GDP per capita (in logs). Column (1) reports results from cross-sectional regression of the period means, with robust standard errors in parentheses. The results in the other columns are from panel regressions with double clustered standard errors at county and year level. ***, **, * denote significance at 0.01, 0.05, and 0.10 levels.

TABLE A.5

UAP Sighting and Income in U.S. Counties: Robustness to State-by-Year Fixed Effects

	(1)	(2)	(3)
$income_{it}$	-1.054***		
	(0.346)		
$income_{it-1}$		-1.369***	-0.939***
		(0.367)	(0.261)
UAP_{it-1}			0.367***
			(0.080)
$state-by-year\ effect$	Yes	Yes	Yes
$county\ effect$	Yes	Yes	Yes
$year\ effect$	Yes	Yes	Yes
$population$	No	No	No
$density$	Yes	Yes	Yes
$weather$	Yes	Yes	Yes
Obs.	46,506	43,890	43,907
R^2	0.744	0.756	0.778

Notes: The table reports coefficient estimates from U.S. county-level regressions, based on specification (1) and controlling for state-by-year fixed effects. The regressions apply annual data for the period of 2000-2017. Double clustered standard errors at county and year level are in parenthesis. ***, **, * denote significance at 0.01, 0.05, and 0.10 levels.

TABLE A.6

UAP Sighting and Income in U.S. Counties: Robustness to suicide rates

	Between County			Within County		
	(1)	(2)	(3)	(4)	(5)	(6)
$income_{it}$	1.885***	2.588***		-3.523***		
	(0.431)	(0.499)		(0.774)		
$income_{it-1}$			0.270**		-3.722***	-2.213***
			(0.131)		(0.812)	(0.623)
UAP_{it-1}			0.818***			0.437***
			(0.049)			(0.063)
$suicide_{it}$	-0.040***	-0.113***	-0.020***	0.026***	0.027***	0.017**
	(0.009)	(0.025)	(0.007)	(0.007)	(0.008)	(0.006)
$county\ effect$	No	No	No	Yes	Yes	Yes
$year\ effect$	No	No	No	Yes	Yes	Yes
$population$	Yes	Yes	Yes	No	No	No
$density$	Yes	Yes	Yes	Yes	Yes	Yes
$weather$	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	19,018	19,018	18,051	18,5617	17,639	17,639
R^2	0.215	0.229	0.735	0.745	0.754	0.802

Notes: The table reports coefficient estimates from U.S. county-level regressions, based on specification (1) and controlling for suicide rates. The regressions apply annual data for the period of 2000-2017. The suicide variable is the annual number of suicide cases per 100,000 people. Annual observations with less than 10 suicide cases (but above zero) are not published and therefore excluded. Column (1) reports results from cross-sectional regression of the period means, with robust standard errors in parentheses. The results in the other columns are from panel regressions with double clustered standard errors at county and year level. ***, **, * denote significance at 0.01, 0.05, and 0.10 levels.

TABLE A.7
UAP Sighting and Income in U.S. Counties: Robustness to military installations

	Between County			Within County		
	(1)	(2)	(3)	(4)	(5)	(6)
$income_{it}$	2.207***	1.751***		-1.582***		
	(0.363)	(0.299)		(0.377)		
$income_{it-1}$			0.253**		-1.780***	-1.163***
			(0.093)		(0.379)	(0.276)
UAP_{it-1}			0.792***			0.381***
			(0.041)			(0.077)
$military_i$	1.154***	1.136***	0.272***			
	(0.210)	(0.282)	(0.068)			
$county\ effect$	No	No	No	Yes	Yes	Yes
$year\ effect$	No	No	No	Yes	Yes	Yes
$military - year\ effect$	No	No	No	Yes	Yes	Yes
$population$	Yes	Yes	Yes	No	No	No
$density$	Yes	Yes	Yes	Yes	Yes	Yes
$weather$	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	46,540	46,540	43,926	46,524	43,907	43,907
R^2	0.198	0.200	0.708	0.730	0.742	0.781

Notes: The table reports coefficient estimates from U.S. county-level regressions, based on specification (1) and controlling for military installations. The variable $military_i$ is a dummy variable that equals 1 if there are military installations in the county as of year 2008. The regressions apply annual data for the period of 2000-2017. Column (1) reports results from cross-sectional regression of the period means, with robust standard errors in parentheses. The results in the other columns are from panel regressions with double clustered standard errors at county and year level. In the panel regressions the $military$ variable is interacted with the year effect. ***, **, * denote significance at 0.01, 0.05, and 0.10 levels.

TABLE A.8
UAP Sighting and Income in U.S. Counties: Robustness to additional economic variables

Order code	**Order**	**Percent**
1	Mandatory for all persons	8.74
2	Mandatory only for persons in certain areas of the jurisdiction	0.76
3-5	Mandatory only for persons at increased risk in the jurisdiction	6.74
6	Advisory or recommendation	39.79
7	No order	43.96

Notes: The table reports the various COVID-19 orders defined by the U.S. Center for Disease Control and Prevention (CDC). The last column reports the frequency of the orders in the daily CDC database of U.S. counties for the year 2020. Order codes 3 to 5 are categorized together since they are close to each other in definitions and have low frequencies.