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**Working Paper**

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GLO Discussion Paper, No. 1175

**Provided in Cooperation with:**

Global Labor Organization (GLO)

*Suggested Citation:* Korenok, Oleg; Munro, David; Chen, Jiayi (2022) : Inflation and attention thresholds, GLO Discussion Paper, No. 1175, Global Labor Organization (GLO), Essen

This Version is available at:

<https://hdl.handle.net/10419/265057>

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# Inflation and attention thresholds <sup>\*</sup>

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September 27, 2022

## Abstract

One of the dangers of high inflation is that it can cause firms and households to pay close attention to it. This internalization of inflation can lead to an accelerationist regime, making inflation harder to control. We empirically assess the relationship between attention and the level of inflation for 37 countries. Our measures of attention are constructed either from internet search behavior or the popularity of inflation mentions on Twitter. We find evidence that attention thresholds do exist for the majority of countries in our sample. We also find interesting variability across countries.

**Keywords:** inflation; attention; threshold

**JEL Codes:** E31, E52, E70

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<sup>\*</sup>We thank Akhil Rao for helpful comments and discussion.

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Price stability is that state in which expected changes in the general price level do not effectively alter business or household decisions.

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*Alan Greenspan, 1989*

# 1 Introduction

Why is high inflation dangerous? One answer to this question is that high rates of inflation trigger households and businesses to alter their behavior, causing them to pay more attention to inflation. This internalization of inflation can lead to an accelerationist inflation regime, possibly ending in hyperinflation.<sup>1</sup> If this concern is valid, optimal policy should aim to keep inflation low enough such that households and businesses do not pay attention to it when they are making decisions. Federal Reserve Chair Jerome Powell appeals to this intuition in his 2022 Jackson Hole speech:

”When inflation is persistently high, households and businesses must pay close attention and incorporate inflation into their economic decisions. When inflation is low and stable, they are freer to focus their attention elsewhere.... Of course, inflation has just about everyone’s attention right now, which highlights a particular risk today: The longer the current bout of high inflation continues, the greater the chance that expectations of higher inflation will become entrenched.” Powell (2022)

In thinking about the optimal rate of inflation, an important policy question involves understanding the level at which households and businesses start paying attention to, and internalizing, the rate of inflation. Knowing this threshold could help central banks avoid entering an accelerationist regime. This may be especially relevant given the shift towards average inflation targeting and recommendations of raising the inflation target.

In this paper we empirically investigate if and where attention thresholds exist. In particular, we proxy for the attention that inflation receives via the frequency of Google searches for “inflation”. For a set of 37 countries, using this measure of attention and actual inflation rates, we estimate the threshold at which the relationship between attention and actual inflation changes. The underlying intuition here is that when inflation is low and people do not pay attention to it, searches should be uncorrelated with actual inflation, while at higher inflation rates, searches should be positively correlated with inflation. Using threshold regressions we explore if such nonlinearities exist in the data, and, more importantly, at what levels of inflation these structural breaks occur, i.e. at what level of inflation does the public start paying attention to it?

We find strong evidence of attention thresholds across a broad set of countries, and that typical thresholds are between 2-4% inflation. We also find that results for some countries are not consistent with an attention threshold interpretation. Notably, for high inflation countries (e.g. Turkey) there is no evidence of an “inattention” regime. As a robustness check we also show that the results are

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<sup>1</sup>For an elegant theoretical formalization of this see Evans and Ramey (1995).

consistent when using an independent measure of inflation: the popularity of “inflation” mentions on Twitter.

Our paper relates to a number of literatures. The theory of rational inattention posits that inattention may be optimal due to costly cognitive resources, and links actual inflation to the attention it receives from households and businesses (Sims (2003), Maćkowiak and Wiederholt (2009), Sims (2010)). When inflation is high, households and firms pay close attention to it, while when inflation is low, they pay no attention to it.

Most empirical studies that support inattention are indirect. They show that inattention better fits aggregate moments (Mankiw and Reis (2007), Maćkowiak and Wiederholt (2015)), that forecasts respond incompletely to new information (Carroll (2003), Andrade and Bihan (2013), Coibion and Gorodnichenko (2015)), or that in experiments people change forecasts when provided with new information (Armantier et al. (2016)) and that the change is larger in a high inflation country compared to a low inflation country (Cavallo et al. (2017)).

We are aware of only two empirical studies that provide direct evidence about attention to inflation: Coibion et al. (2018) and Bracha and Tang (2022). In particular, based on a survey of firms in New Zealand, Coibion et al. (2018) report that most firms see inflation as unimportant in their business decisions and do not pay attention to its recent values. They also report that firms have little incentive to pay attention to inflation, except when news reports about inflation are negative (substantial increases in inflation). Bracha and Tang (2022) measure the level of inattention as the proportion of Michigan Consumer Survey participants that are not aware of the current level of inflation. They report greater inattention when inflation is lower, and that this link is statistically significant. To illustrate, they report that in the U.S., the level of inattention doubled post-2007, when average inflation was 1.9 percent, compared to the pre-1993 period, when average inflation was 4.1 percent. Bracha and Tang (2022) find similar evidence in European data showing a negative and significant relationship between inflation and the proportion of survey participants that are not aware of its current level.

## 2 Empirics

### 2.1 Data and Methodology

The approach we take to empirically assess the existence of different attention regimes is to estimate a threshold model. Consider the following single-threshold fixed effect panel model:

$$y_{it} = \alpha + x_{it}(x_{it} < \gamma)\beta_1 + x_{it}(x_{it} \geq \gamma)\beta_2 + u_i + e_{it}, \quad (1)$$

Our interest is in understanding how attention given to inflation varies with the level of inflation. As such,  $y_{it}$  is our measure of attention in country  $i$  period  $t$  and  $x_{it}$  is the official measure of inflation in country  $i$ . Our threshold variable is also  $x_{it}$ .  $\gamma$  is the threshold parameter that separates two regimes: the first regime occurs when  $x_{it} < \gamma$  and has a coefficient of  $\beta_1$ ; the second regime occurs when  $x_{it} > \gamma$  and has a coefficient of  $\beta_2$ ;  $u_i$  is a country  $i$  error term, while  $e_{it}$  is the overall error term. As a starting point, we estimate  $\gamma$  via panel regression, but we also explore single country threshold estimates to explore heterogeneity in these thresholds. To empirically estimate these thresholds involves searching across different candidate thresholds and choosing the value which

best fits the data.<sup>2</sup>

We obtained official monthly inflation data from the OECD Prices: Consumer Prices database. From Google Trends, we obtained monthly indices for the historical volume of searches for the term “inflation” from 2004 to May 2022. For each country we obtain these indices for the most popular languages. In particular, we used the most popular languages so that this set of languages covers at least 75% of the population.<sup>3</sup> The appropriate search terms for “inflation” in other languages were obtained from Google Translate. A number of countries had data limitations in Google Trends. For example, there was no recorded data for “inflation” in Hebrew, Israel’s most common language, so Israel was excluded from the data. In addition, some countries do not use Google widely, e.g. China and Russia, as such we also exclude such countries from the dataset. Provided in the Table A.1 in the Appendix is a full list of the 37 countries for which we were able to collect Google Trends data.

## 3 Results

### 3.1 Panel Estimate

We begin by estimating attention thresholds from the full panel of countries using (1). Results are reported in the first column of Table 1. The estimated threshold for inflation rate is  $\hat{\gamma} = 2.09$ . Below this threshold, there is no significant relationship between the level of inflation and Google searches ( $\beta_0 = 0.098$ , p-value = 0.482). Above this threshold, the relationship between inflation and searches is ten times larger and is significant ( $\beta_1 = 1.32$ , p-value = 0.000). The threshold model is statistically significant relative to a simple linear model without a threshold (F-stat=83.22, p-value=0.013).<sup>4</sup> We also investigate if the data supports more than one threshold and do not find evidence of multiple thresholds. The double and triple threshold models are not significantly different from a no-threshold linear model.<sup>5</sup>

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<sup>2</sup>This involves searching over candidate  $\gamma$ ’s and finding the one which minimizes the sum of square residuals. For more information on the approach to estimate  $\gamma$ , see Wang (2015).

<sup>3</sup>For example, if a country’s primary language is spoken by 60% of the population, we would also collect data for the second most popular language. If these two languages in aggregate accounted for 75% of the population we would stop at the second language, otherwise we would add the third, and so on.

<sup>4</sup>If we exclude the most recent spike in inflation after January 2020, the estimated threshold is unchanged at 2.09 with a p-value from an F-test against a null of a no threshold linear model of 0.03.

<sup>5</sup>It is possible that a second threshold would exist in deflationary episodes, however, in practice deflation episodes are so rare in the data that it would be hard to detect.

	All Countries	U.S.
$\gamma$	2.09**	3.55***
p-value (F-test)	0.013	0.000
$\beta_1$	0.098 (0.139)	0.514 (0.374)
$\beta_2$	1.324*** (0.041)	10.12*** (0.628)
N	8140	220

Table 1: Results from fixed effects panel threshold model. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Below each  $\gamma$  we report p-value from F-tests of the null hypothesis that the threshold model provides no statistical improvement over a no-threshold linear model.

These initial results can be interpreted as follows: below the inflation rate of 2.09% people do not pay attention to inflation, as a result, changes in inflation have no relationship with the frequency of inflation searches; while above the threshold, people start paying attention to inflation reflected as a higher number of searchers as inflation rises, and as a result, there is a positive and significant relationship between inflation and search behavior.<sup>6</sup> It is interesting that our estimate of the threshold is close to the conventional inflation target of 2%.

### 3.2 Individual Country Estimates

While the baseline panel regression is a useful starting point, a natural question is to ask about heterogeneity in these thresholds across countries. To explore this, we re-estimate (1) for each country. As an example, we begin with the results from the U.S., presented in the second column of Table 1. The estimated threshold for the U.S., 3.55% is somewhat higher than the one estimated from the panel regression, 2.09%.<sup>7</sup> In addition, consistent with the panel results, there is no significant relationship below the threshold and a positive and statistically significant one above.

A visual depiction of the threshold model along with the raw data for the U.S. is presented in Figure 1. The U.S. results align very well with an attention threshold interpretation. The figure demonstrates a lack of dependence between level of inflation and number of Google searches below the threshold (red line). It also shows a strong positive relation between the two variables after the threshold (green line).

<sup>6</sup>This interpretation is in line with Coibion and Gorodnichenko (2015) results that report that firms pay little attention to inflation, except during periods when news reports are negative

<sup>7</sup>The threshold model for the U.S. is significant relative to a linear model ( $p\text{-value} < 0.01$ ).

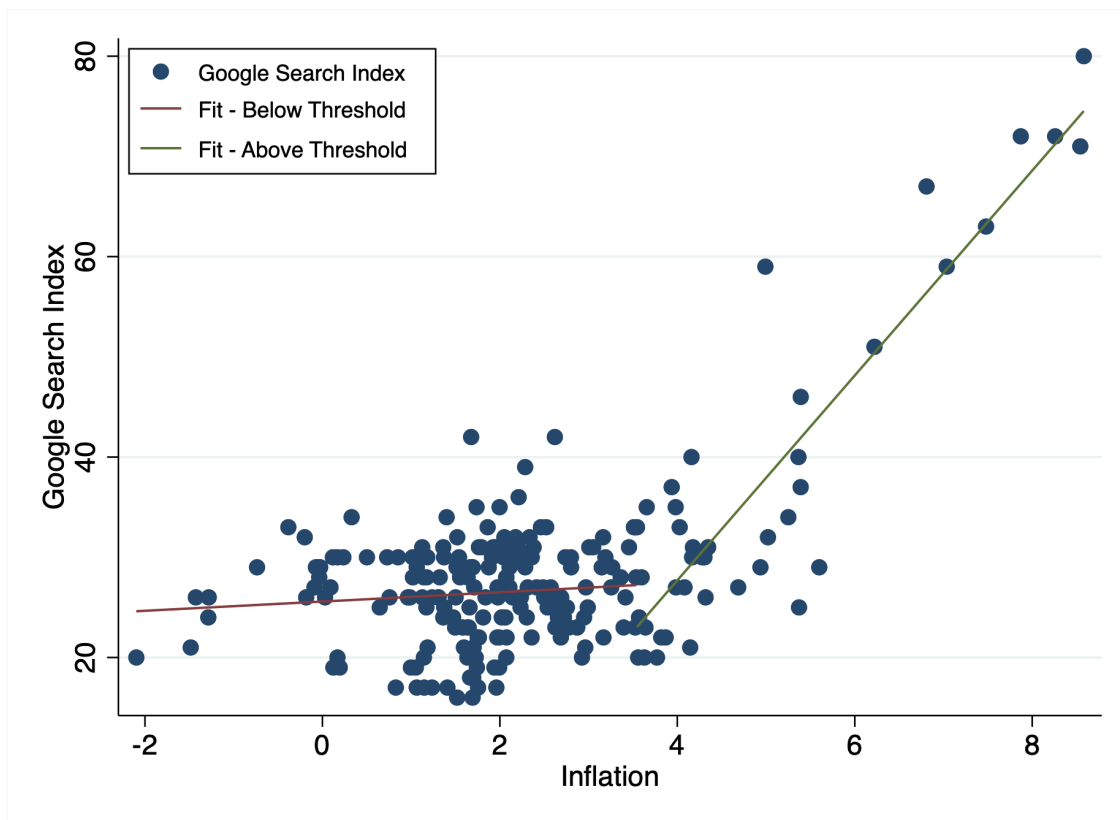


Figure 1: Threshold model fit for the U.S. ( $\hat{\gamma} = 3.55$ )

Our result is in line with Rudd (2021) who observes highly persistent inflation dynamics when trend inflation in U.S. was four percent, and not persistent dynamics with two percent trend inflation.

Next we turn to the estimates of thresholds for the other countries. Figure 2 plots a histogram of the estimated thresholds for all 37 countries in our dataset. In line with the panel estimate, the majority of countries have threshold estimates between 2% and 4%, while only a few countries have thresholds above 5%. The maximum threshold (for Turkey) is 9.48%.

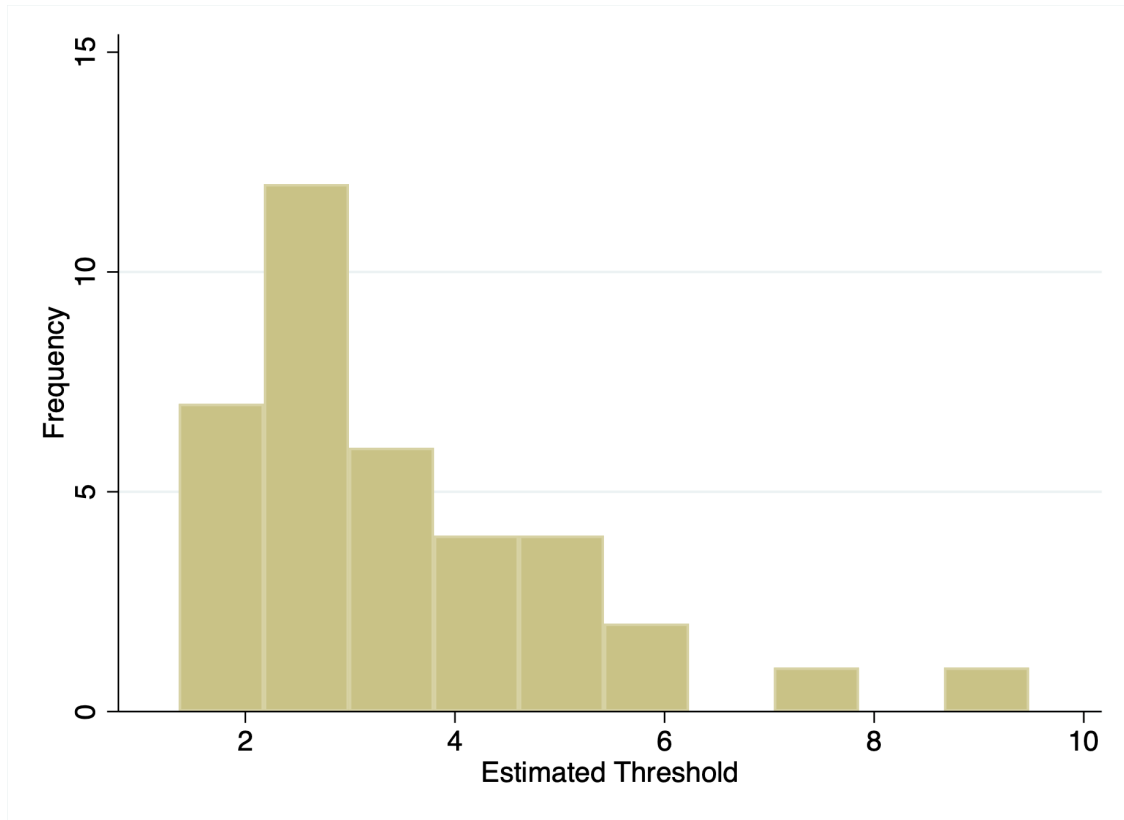


Figure 2: Histogram of Threshold Estimates

Figure 3 illustrates more countries whose results are similar to the U.S: with no significant relationships below the threshold and a positive and significant relationship above the threshold.



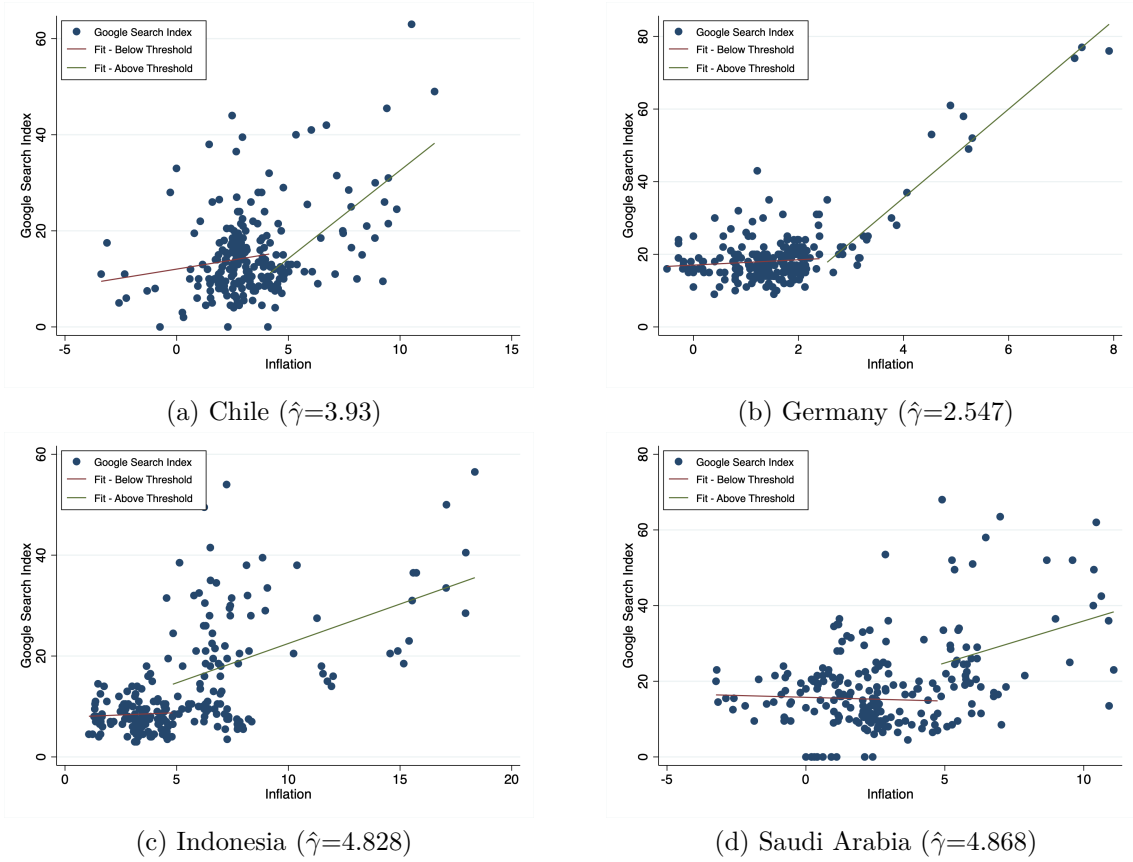


Figure 3: Other individual country examples of threshold model results

To give a general sense of the estimates of  $\beta_0$  and  $\beta_1$  for each country we summarize them graphically. In Figure 4, for each country, we plot  $\hat{\beta}_0$  on the y-axis and  $\hat{\beta}_1$  on the x-axis. A 45-degree line is plotted as a dashed red line indicates where  $\hat{\beta}_0 = \hat{\beta}_1$ . Dots below the 45-degree line and to right of the origin on the x-axis indicate countries where  $\hat{\beta}_1 > \hat{\beta}_0$ , in other words, where the relationship between attention and inflation is stronger above the threshold.<sup>8</sup> The abundance of dots below the 45-degree line and with positive values of  $\hat{\beta}_1$  highlight that a large share of countries have threshold model estimates consistent with an increase attention above the threshold.

<sup>8</sup>Each dot is shaded according to the F-statistic from the test of the threshold model fit vs. a no-threshold linear model. So darker points indicate better threshold model fits.

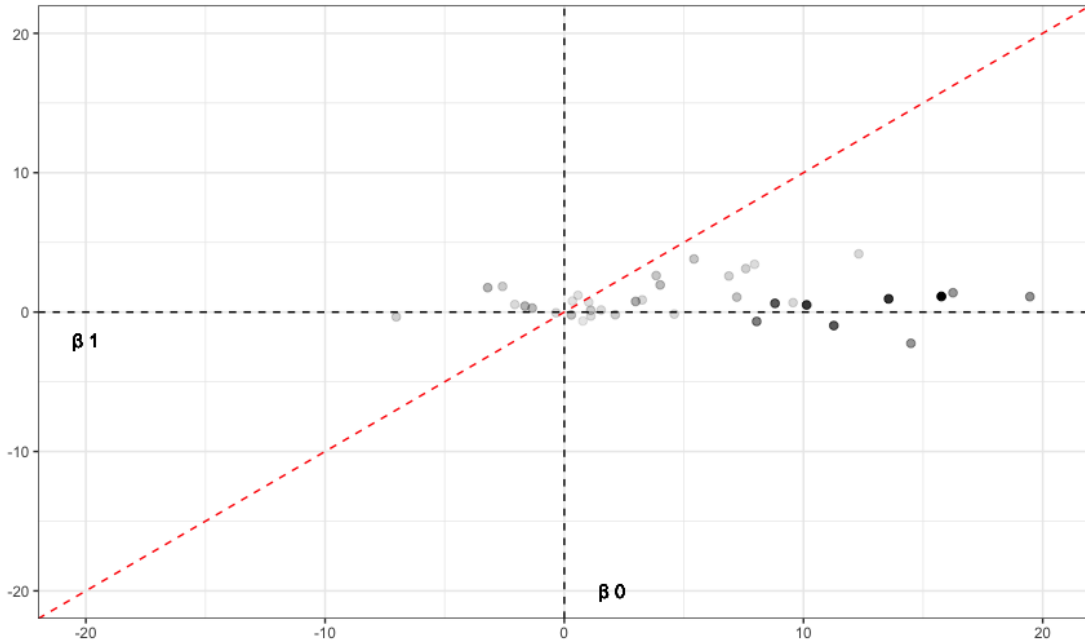


Figure 4:  $\hat{\beta}_0$  and  $\hat{\beta}_1$  Estimates

Next, we classify each country as either “Consistent with U.S.,” when a country has an insignificant slope below the threshold and a significant positive slope above the threshold; “Intermediate” when a country has a small positive slope below the threshold, but a statistically larger slope above the threshold; and “Not Consistent with U.S.” for all other cases. We report results of this classification in Table 2 and plot all individual country results in Appendix A.1 for reference.

Consistent with U.S.	Intermediate	Not Consistent with U.S.
Austria (1.99)	Canada (1.88)	Brazil (5.75)
Belgium (2.02)	Czechia (2.47)	Columbia (4.26)
Chile (3.34)	Finland (1.42)	Estonia (3.32)
Denmark (1.51)	Italy (1.51)	Greece (1.49)
France (1.34)	Korea (2.19)	Hungary (3.75)
Germany (1.58)	Mexico (4.25)	Ireland (1.24)
Iceland (4.61)	Netherlands (1.75)	Japan (0.27)
Indonesia (5.60)	Poland (2.43)	Slovenia (1.91)
Latvia (3.83)	Portugal (1.45)	Switzerland (0.36)
Lithuania (3.17)	Slovakia (2.60)	Turkey (11.00)
Luxembourg (1.92)	Spain (1.87)	
Norway (2.09)	UK (2.18)	
Saudi Arabia (2.84)		
Sweden (1.25)		
US (2.29)		
Avg. Inflation =2.63	Avg. Inflation=2.23	Avg. Inflation=3.33

Table 2: Classification of Country Threshold Results. Average rates of inflation over the time period are reported in parentheses.

While the intermediate group includes countries whose results are not quite as strong as those for the U.S., results for these countries are still consistent with the rational inattention interpretation of lower attention for lower levels of inflation and higher attention for higher levels of inflation.

In Figure 5 we plot four examples of countries classified as “Intermediate.” A number of these Intermediate countries look visually similar to the U.S., in particular, Canada and Finland. The main difference causing these countries to be classified as Intermediate is that we can reject the null hypothesis of no relationship between attention and inflation below the threshold. But it is also worth pointing out that in a number of countries these slopes, while significant, are quantitatively small pointing to a weak link between attention and inflation. For example, Canada and Finland both have positive and significant estimates of  $\hat{\beta}_0$  but their estimates of  $\hat{\beta}_1$  are 14 and 12 times larger, respectively. Large increases in the slopes above the threshold still provide evidence that that relationship becomes substantially stronger at higher levels on inflation.

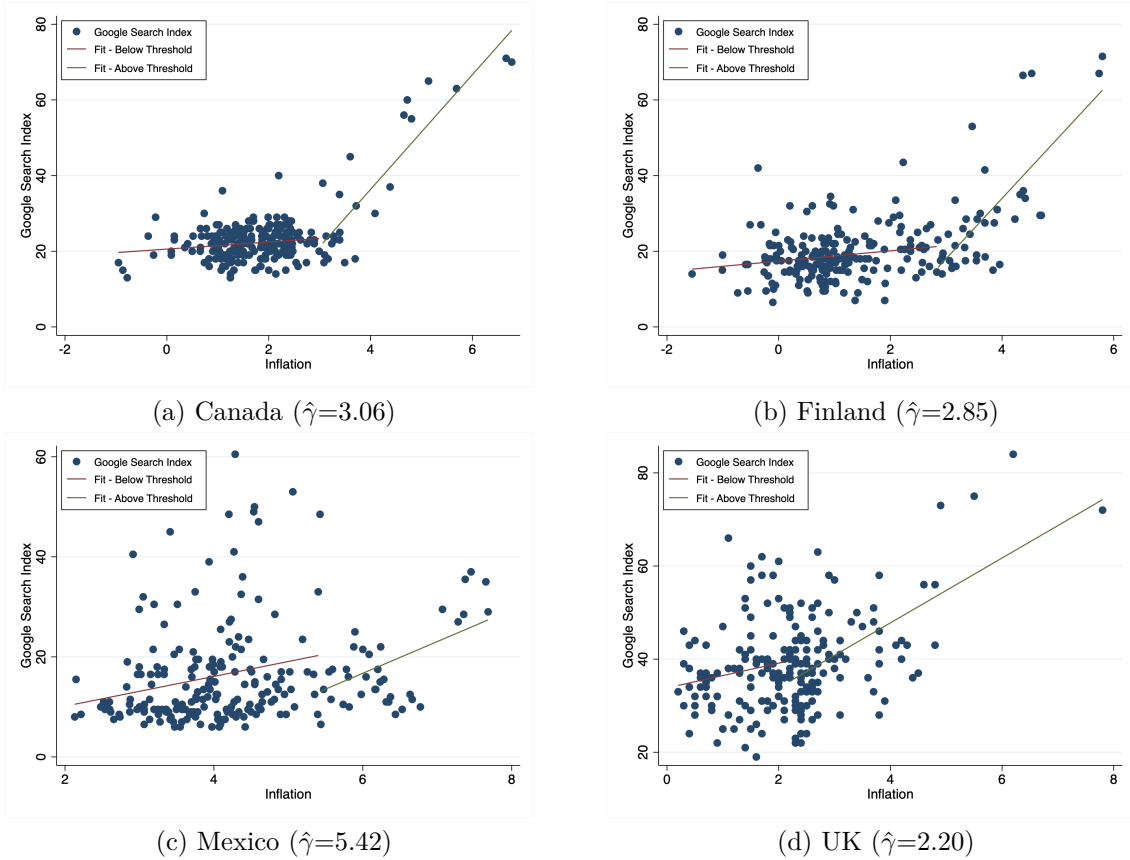


Figure 5: Examples of countries classified as Intermediate.

Turkey in Figure 6 is an example of a country which does not fit the inattention theory. The relationship between the level of inflation and attention is significant both below and above the threshold and it is actually stronger below the threshold. We also fail to reject no improvement in model fit between a linear model versus the threshold model plotted in Figure 6 (F-stat=1.023, p-value=0.433). These results point to strong attention to inflation even at low levels of inflation. Note, however, that Turkey has the highest average inflation rate of all countries in our sample, and one interpretation of these results is that these high rates of overall inflation prevent households and firms from entering an inattention regime. There are other high inflation countries in the “Not Consistent” classification. For example, Brazil (5.75%), Columbia (4.26%), and Hungary (3.75%). However, there are also very low inflation countries that are classified as “Not Consistent”. Inflation rates of these countries never get very high, even in the most recent period (post-2020). For example, the maximum inflation rates for Japan and Switzerland over the entire time series are 3.7% and 3.07%, respectively. A lack of evidence for a threshold in these countries could be because they simply have not experienced inflation rates high enough to trigger the change in attention regimes.

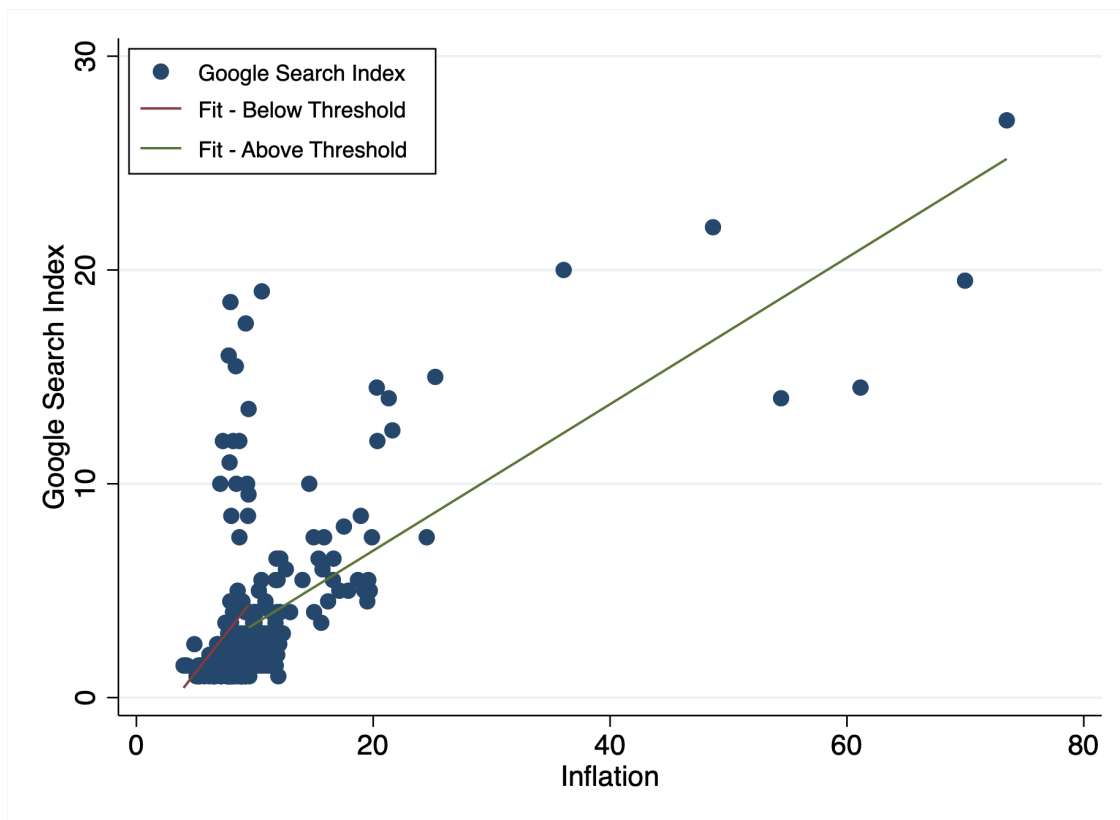


Figure 6: Threshold model fit for Turkey ( $\hat{\gamma} = 9.48$ )

### 3.3 Robustness

Google searches are, of course, but one proxy for attention. We chose this proxy, as Google is widely used as a search engine internationally and the search frequency indices begin in 2004, giving a relatively long time series. As a robustness check we also explore evidence of attention thresholds using a different proxy for attention: the frequency of tweets containing the word “inflation.”<sup>9</sup> As an attention proxy, count of tweets is more limiting. First, the data is only available back to 2011; second, Twitter is not nearly as popular internationally; lastly, only around 2% of Twitter users choose to reveal location information (which we need to assign the country of origin), which leads to small sample sizes and selection questions.

We restrict our attention to a subset of countries that have at least 5% of the population having Twitter accounts in 2012, around when the data begins.<sup>10</sup> There are 15 countries that meet this criteria. As an example, we again show the threshold estimation results for the U.S. in Figure 7.

<sup>9</sup>Because the popularity of Twitter has changed over time, we normalize the count of monthly “inflation” tweets. Our normalizing factor was the total number of tweets occurring between 9 and 9:30 AM on the first Monday of the month (total number of tweets in a month was computationally very costly). As an additional robustness check we tested expanding this window to over 12 hours and it did not materially impact the results.

<sup>10</sup>See, Dawson (2012).

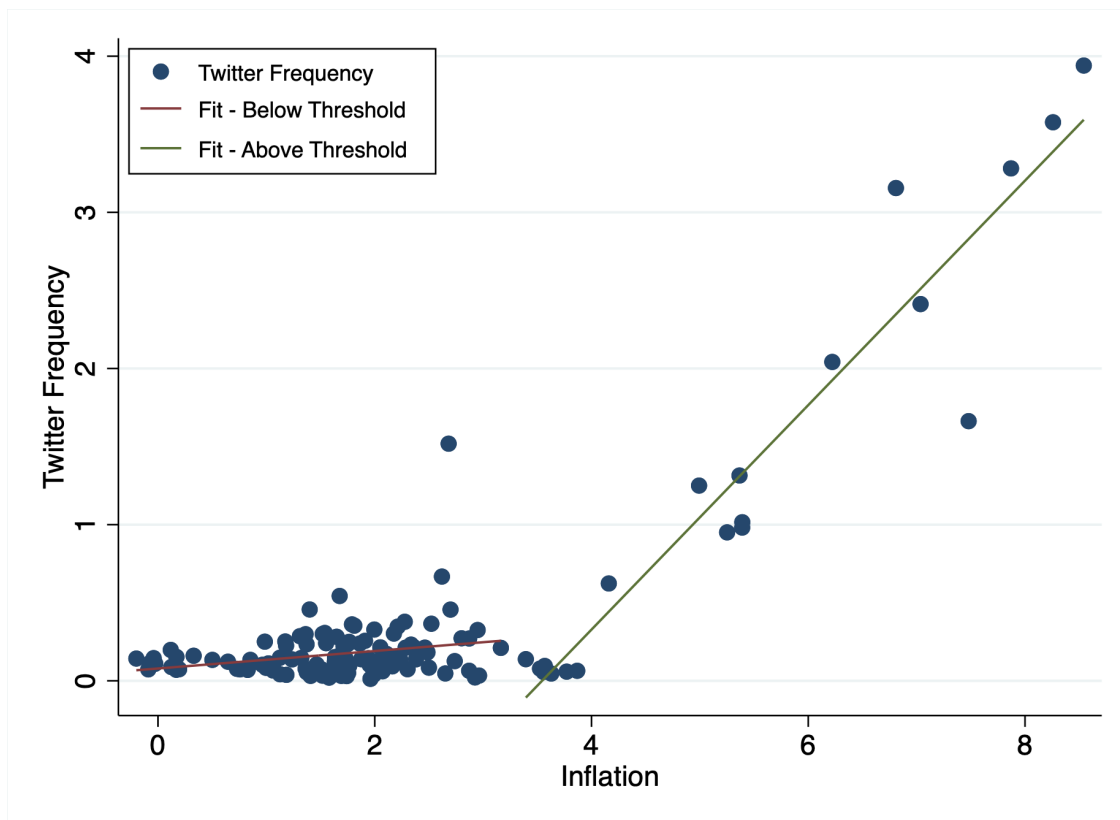


Figure 7: Threshold model fit for the U.S. using Twitter data. ( $\hat{\gamma} = 3.39$ )

The estimated threshold for the U.S. is 3.39. We re-estimate the threshold model using the Google data on the same time window to provide an apples-to-apples comparison and this yields an estimated threshold of 3.16. For all the countries in the Twitter data that meet either the “Consistent with U.S.” or “Intermediate” criteria, we summarize how the thresholds estimated using the Twitter data compare to those from Google in Table 3. Overall, these two proxies for attention yield very similar threshold estimates and model fits, plotted in Appendix A.2.

Country	$\hat{\gamma}$	
	Twitter	Google (post-2010)
Canada	3.17	3.17
Chile	4.99	3.80
France	1.89	2.25
Germany	2.17	1.92
Indonesia	3.47	5.10
South Korea	2.49	2.28
Mexico	6.16	6.16
Netherlands	2.88	2.88
Spain	2.97	2.88
U.K.	2.50	2.30
U.S.	3.39	3.16

Table 3: Comparison of threshold estimates between Twitter and Google data.

Also consistent across both attention proxies are some of the countries that we classify as “Not consistent with U.S.” For example, for Turkey and Japan results look quite similar when using either the Google or Twitter attention proxies. Some notable improvements in model fit occur for Brazil and Columbia, plotted in Appendix A.2. These two countries both now show some evidence consistent with attention thresholds. Overall, using Twitter data as an alternative proxy for attention generates results that align quite well with those generated from Google data.

## 4 Discussion

The main objective of our paper is to explore (in)attention towards inflation. We find strong evidence that in many countries below a threshold people pay no attention to inflation, while above the threshold they pay close attention. We also report that in some countries this is not the case; people pay attention to inflation independent of inflation level.

Our results provide general empirical support for theories of rational inattention (RI). Some RI models<sup>11</sup> predict that when agents’ prior variances are below the cost-benefit ratio, agents are inattentive to inflation. When agents are inattentive, there should be no relation between measures of attention and inflation. Indeed, there are a number of countries for which we observe this empirical prediction, specifically, those classified as “Consistent with U.S.” We would like to caution, however, that our evidence is reduced form. We do not measure either prior variances or cost-benefit ratios, which, according to the theory of RI, determine attention thresholds. These priors and cost-benefit ratios could, of course, depend on the current level of inflation, which is our focus. However, priors and cost-benefit ratios are also more difficult to measure in field data.

Our results also provide empirical support for the model of Evans and Ramey (1995). In their model, agents choose how many periods into the future to make inflation calculations about. They cease making the  $n$ th-step-ahead computation when the cost of further computations outweighs the expected benefit of reducing forecast errors. In their model, inflation stays in a stable regime when

<sup>11</sup>In particular, a version of Sims (2003) model discussed in Bracha and Tang (2022))

agents do not pay enough attention to (make enough computations about) inflation. This could be viewed as generally consistent with the evidence from countries in the "Intermediate" classification: below the critical threshold agents still respond to changes in inflation (a positive relationship), but at higher levels of inflation they are more responsive.

Our findings are also in line with previous empirical results that study direct measures of attention. They are consistent with the results from Coibion et al. (2018) which show that during periods of low inflation (below-2%) most firms in New Zealand did not pay attention to inflation and considered it as unimportant in their business decisions. Our results showing a positive and significant relationship between attention and inflation are consistent with the results in Bracha and Tang (2022). They find a negative and significant correlation between the proportion of people who do not know the current inflation level in Michigan survey and the actual level of inflation.

There is a rich literature in behavioral macroeconomics which examines how past experiences shape future behavior.<sup>12</sup> In the context of inflation and attention, an interesting question relates the degree to which agents in the economy become habituated to past levels of inflation. For example, 4-5% inflation may seem unusual to households and firms who have not experienced above 2% inflation, while the same 4-5% might not trigger changes in attention in countries that routinely experience inflation at this level.<sup>13</sup> We investigate this question by looking at the relationship between estimated thresholds and average inflation rates for each country in Figure 8.<sup>14</sup> This figure shows a strong positive relationship: the thresholds are at the higher levels in countries that experience higher rates of inflation. These results are generally consistent with a habituation story.

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<sup>12</sup>For an important early contribution see Malmendier and Nagel (2011).

<sup>13</sup>For some behavioral evidence on the importance of reference points (losses) for attention provision, see Carpenter and Munro (2022).

<sup>14</sup>We restrict our attention to countries classified as "Consistent with U.S." or "Intermediate" because it does not seem appropriate to use estimated thresholds that are inconsistent with attention regime interpretation.



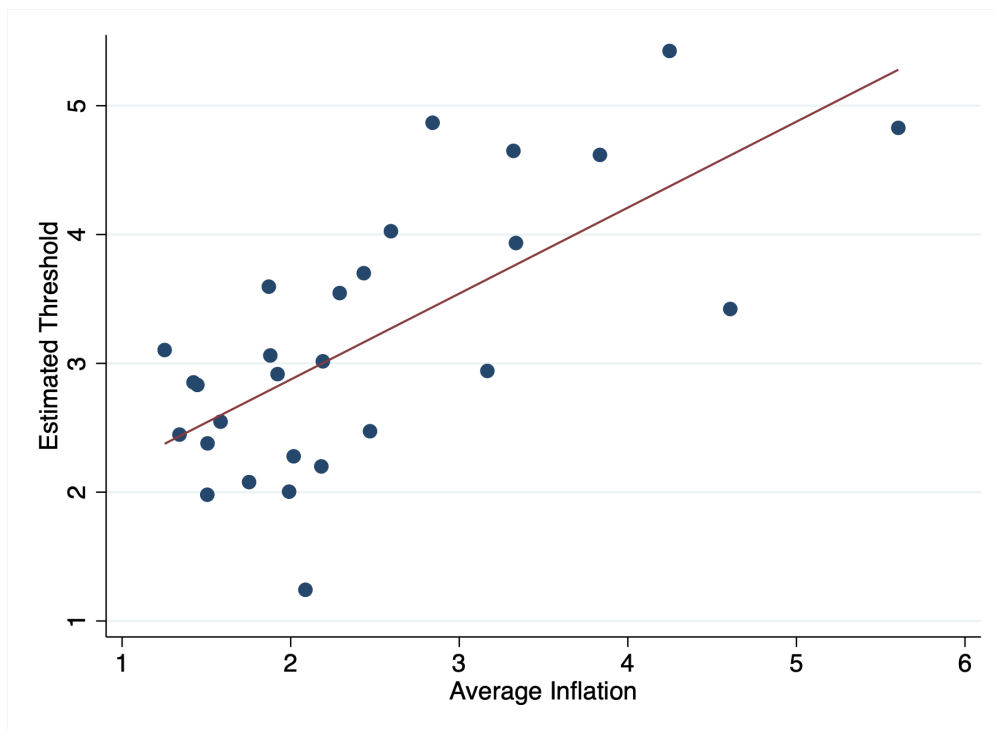


Figure 8: Estimated thresholds and average inflation rates

These habituation results are interesting in thinking about optimal inflation target. New Zealand’s central bank adopted 2% target with little debate. Over time, 2% became standard target, justified by pointing to a success of early adopters. Many researchers advocate raising the target (e.g., Blanchard et al. (2010), Ball (2013)). Our results on one hand suggest that raising the inflation target and inflation risks increasing attention of households to inflation causing inflation to persist. On the other hand, if higher inflation comes as a surprise, is there a time horizon where that attention starts to fade? Further, as the case of Turkey possibly highlights, what level of inflation, or variance of inflation, causes a country to enter a permanent attention regime? These are important questions that need to be addressed before choosing optimal inflation target.

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# A Empirical Appendix

## A.1 Individual Country Threshold Model Results Using Google Trends Data

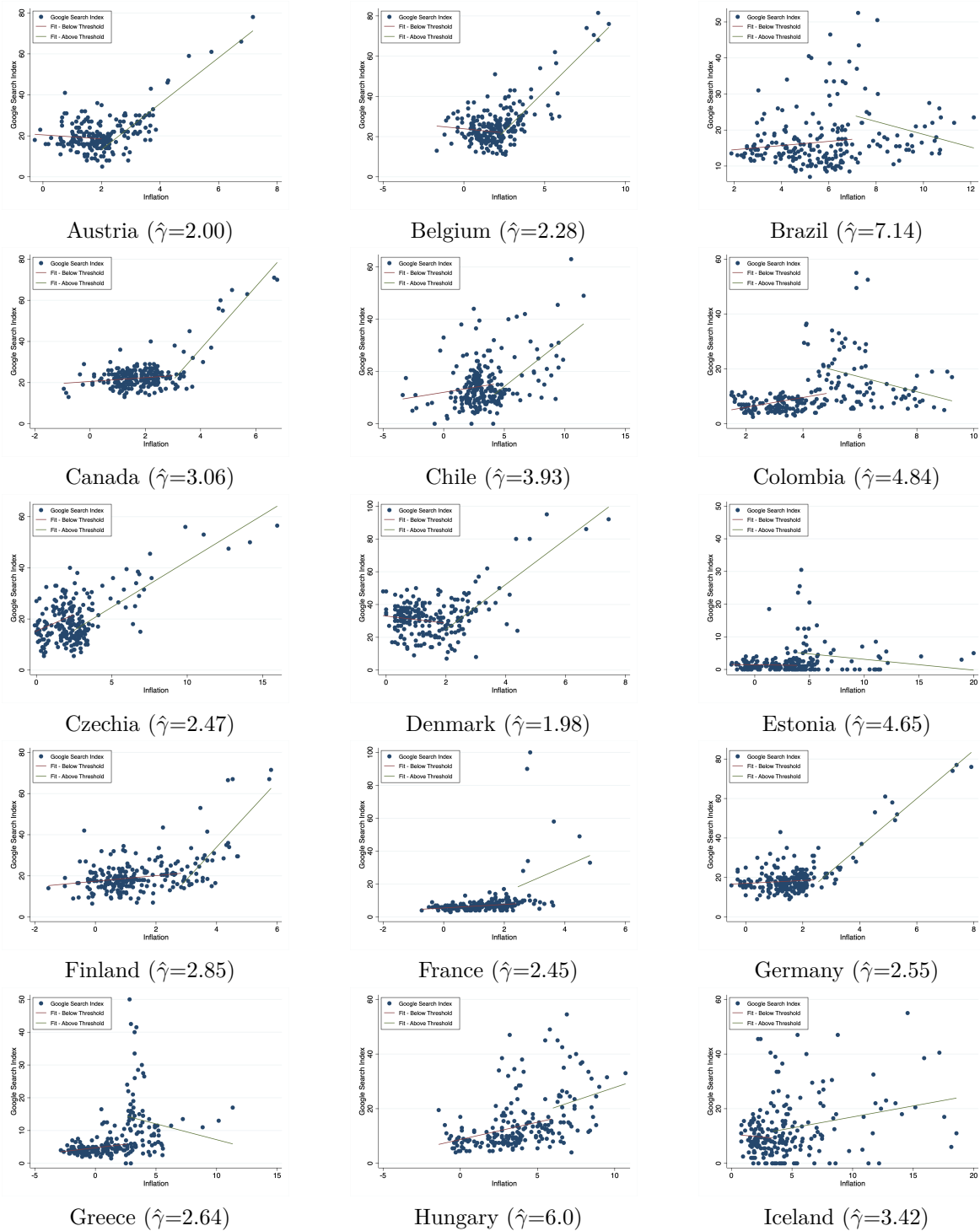


Figure A.1: Threshold model results for individual countries

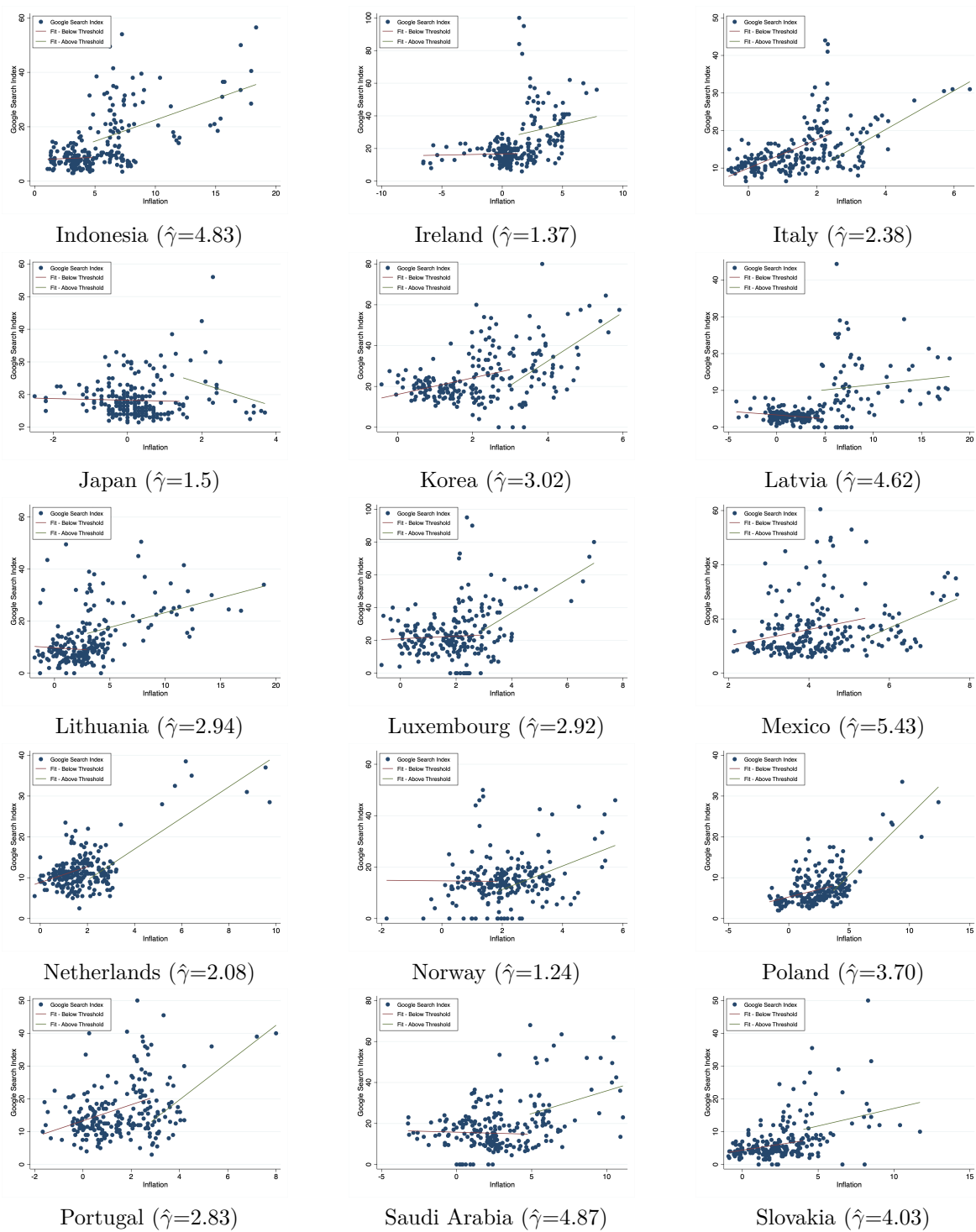
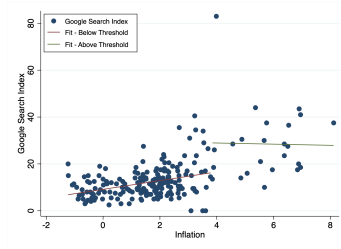
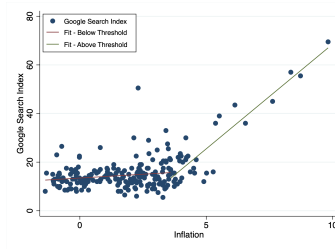


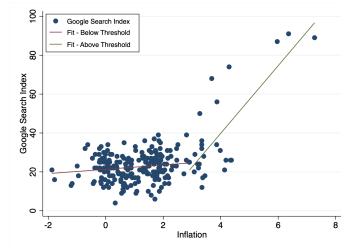
Figure A.1: Threshold model results for individual countries



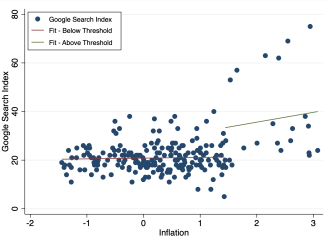
Slovenia ( $\hat{\gamma}=3.85$ )



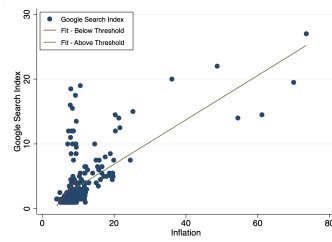
Spain ( $\hat{\gamma}=3.60$ )



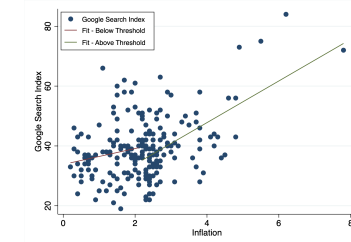
Sweden ( $\hat{\gamma}=3.10$ )



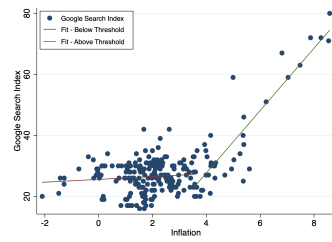
Switzerland ( $\hat{\gamma}=1.44$ )



Turkey ( $\hat{\gamma}=9.48$ )



U.K. ( $\hat{\gamma}=2.20$ )



U.S. ( $\hat{\gamma}=3.55$ )

Figure A.1: Threshold model results for individual countries

## A.2 Individual Country Threshold Model Results Using Twitter Data

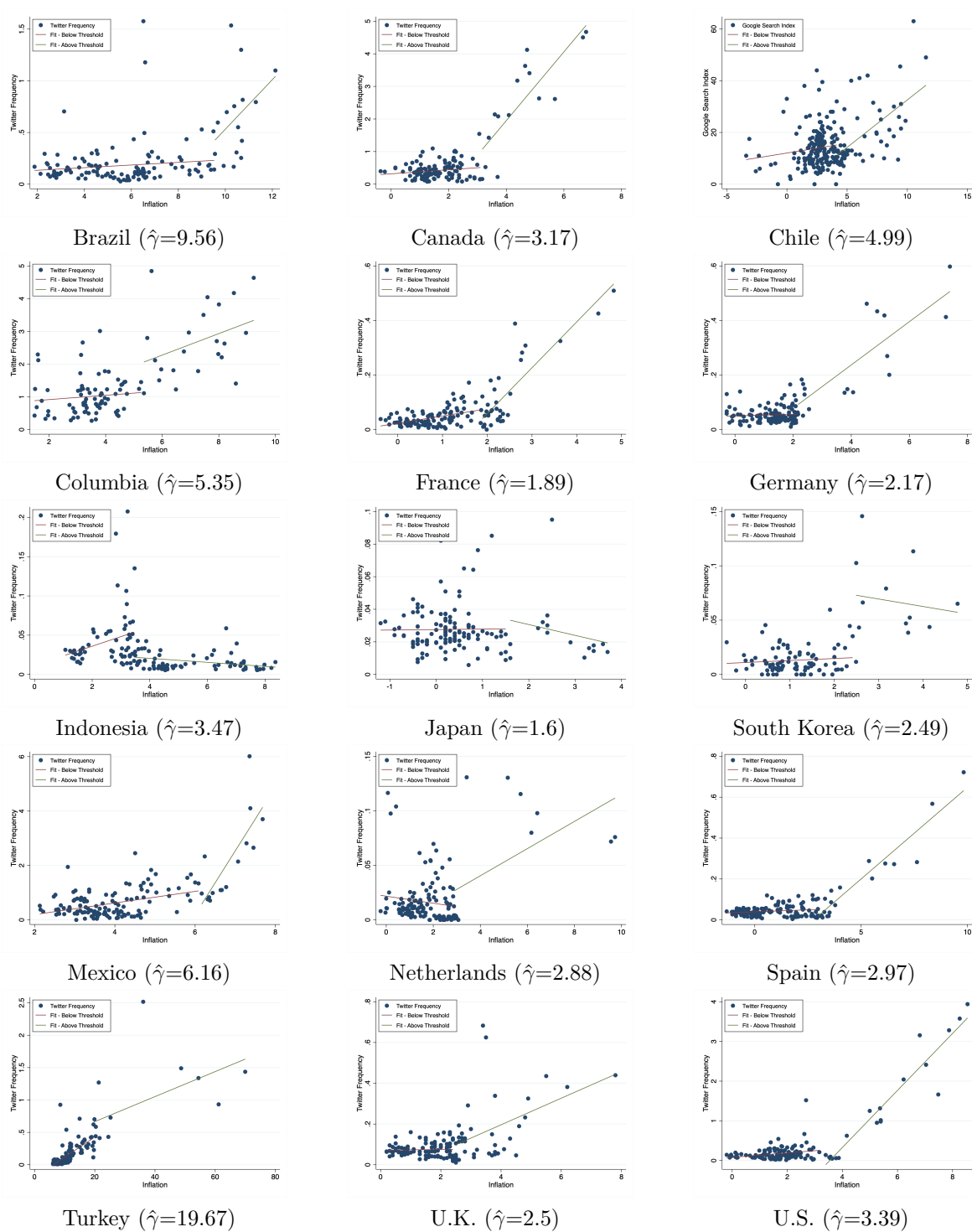


Figure A.2: Threshold model results for individual countries using Twitter data

### A.3 Countries and Languages

Here we list the languages we used to collect data for each country. As noted in the main text we collected languages such that they accounted for at least 75% of the country. It should also be noted that the English word “inflation” is spelled the same in French, German, and Danish. Because of this, when we retrieve data for “inflation” searches in Germany, for example, we are also capturing search behavior of English, French, and Danish speakers. In light of this, to be consistent across countries, in addition to the languages listed in the table below, we also retrieve the data for “inflation” in each country. For each country we average across all languages in each month to obtain a single time series. The way Google normalizes multiple series, less popular languages are weighted according to their average search frequency over the sample. Google normalizes the maximum monthly search frequency to 100 and all other months are indexed to relative to that. As a result, each language will be weighed according to its overall popularity in searches.



Country	Language 1	Language 2
Austria	German	
Belgium	Dutch	French
Brazil	Portuguese	
Canada	English	
Chile	Spanish	
Colombia	Spanish	
Czechia	Czech	
Denmark	Danish	
Estonia	Estonian	
Finland	Finnish	
France	French	
Germany	German	
Greece	Greek	
Hungary	Hungarian	
Iceland	Icelandic	
Indonesia	Indonesian	
Ireland	English	
Italy	Italian	
Japan	Japanese	
South Korea	Korean	
Latvia	Latvian	Russian
Lithuania	Lithuanian	
Luxembourg	French	
Mexico	Spanish	
Netherlands	Dutch	
Norway	Norwegian	
Poland	Polish	
Portugal	Portuguese	
Saudi Arabia	Arabic	
Slovakia	Slovak	
Slovenia	Slovenian	
Spain	Spanish	
Sweden	Swedish	
Switzerland	German	French
Turkey	Turkish	
United Kingdom	English	
United States	English	

Table A.1: List of languages used in collecting Google Trends and Twitter data.