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Regular article

Psychological price barriers, El Niño, La Niña: New insights for the case of coffee☆

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ABSTRACT

This paper investigates the possibility of psychological barriers in the price dynamics of seven types of coffee varieties over a twenty-year period. When prices are expressed in hundreds of cents, barriers surrounding the round number prices ending in 00 are confirmed for the high quality coffees. The dynamics of coffee price returns differ before and after breaches of hypothesised barriers. Using a novel model selection method based on multiple testing, there is further confirmation of price barriers insofar as positive and negative climate anomalies affect coffee price proximity to barriers.

1. Introduction

There is considerable value in understanding the nature of coffee price fluctuations. As a leading export commodity in world trade, coffee constitutes an important source of foreign exchange, public sector revenue, value-added and employment in low- to upper-middle-income countries located in the tropics (see International Coffee Organization, 2019). The importance of coffee in the area of development economics is perhaps best reflected in the studies which have analysed the macroeconomic effects of world coffee prices on producing countries both analytically (e.g. Cárdenas, 1994; Otero, 2000) and empirically (e.g. Bevan et al., 1987; Montenegro, 1999). A central ingredient in these analyses is the characterisation of coffee price shocks as either transitory or permanent. While such a distinction can shape the optimal response by policymakers, the existing literature provides other valuable insights. The persistence properties of the underlying prices helps characterise the duration and magnitude of coffee booms and slumps.[2] In other directions of research there has been interest on the quantification of pass-through effects, that is, how much domestic prices paid to farmers change when world coffee prices change (see, e.g., Mehta and Chavas, 2008; Russell et al., 2012;

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[2] In this regard, authors such as Deaton and Miller (1996), Cashin et al. (2002), Kellard and Wohar (2006), Ghoshray (2011), Fernandez (2012), Ghoshray (2019) and Winkelried (2021) have studied trends and cycles in coffee (and other commodity) prices, while Vogelvang (1992), Otero and Milas (2001), Ghoshray (2009, 2010), Otero et al. (2018), Holmes and Otero (2020), and Fousekis and Grigoriadis (2017, 2022) have examined the existence of short- and long-run interactions among (spot and futures) prices of coffee types. Fernandez (2014) and Umar et al. (2021), among others, explore co-movements and interdependencies with stock, exchange and other commodity markets.

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Hernandez et al., 2017). Finally, there has been attention to the economic impacts of weather conditions, as measured by El Niño Southern Oscillation (ENSO), on world coffee prices (Ubilava, 2012; Sephton, 2019) and production (Bastianin et al., 2018).

This literature has so far provided a valuable understanding of coffee price dynamics. However, one crucial aspect of the time-series properties of coffee prices that hitherto has not been explored is the possible existence of psychological price barriers. On the part of coffee traders, psychology in the marketplace has the potential to impact the nature and extent of coffee price stability. According to Aggarwal and Lucey (2007) and others, there are psychological aspects of human information processing, and decision-making on the part of traders in financial markets that lead to several behavioural biases occurring when traders fixate on a market price informed commentators may argue is important. The herding behaviour of traders may cluster price expectations around round numbers. Indeed, without agreement on the values of economic fundamentals, many traders may focus on the nearest round number as a reasonable proxy of the price of a product. Gold, for example, is a natural resource historically considered an asset along with bonds and equities, where the psychological aspects of decision-making can be very distinct.

In the case of coffee, little is known about whether such psychology is present as reflected in the pricing behaviour of specialised traders. As with other commodities, an increased financialisation of the coffee market is reflected in a growing volume of investment vehicles that includes coffee futures contracts and coffee-related exchange-traded funds. There is already evidence based on informal references to psychological coffee prices in the media. For example, the Financial Times in 2011 reported that "Arabica coffee prices rose to a 34-year high – fast-approaching the barrier of $3 per pound..." (Financial Times, March 10, 2011). Later that year, the President of the National Association of Colombian Coffee Exporters said the price of coffee, the highest in 34 years, is "unsustainable" as it is not reflecting the current value (Colombia Reports, May 4, 2011). More recently, commentators noted in 2022 that "...having broken through the $2.00/lb psychological barrier, there remains a very strong possibility that it will not be long before this barrier is tested again" (Coffee Industry Corporation Ltd., July 17, 2022).

We hypothesise that psychological coffee price barriers are associated with the possibility of a higher frequency of 00 digits compared to other digit endings. If a particular importance is attached to specific coffee price endings, such as ones, tens, or hundreds, then this form of behavioural bias gives rise to the possibility of rigidities or impediments to the movement of coffee prices, which are not rooted in economic fundamentals.[3]

Psychological price barriers have been the subject of active research in other markets, including exchange rates (De Grauwe and Decupere, 1992), equity and stock prices (Donaldson and Kim, 1993; Koedijk and Stork, 1994; Ley and Varian, 1994; De Ceuster et al., 1998; Cyree et al., 1999; Berk et al., 2017; Lobao and Pereira, 2017), gold prices (Aggarwal and Lucey, 2007), non-ferrous metals prices (Cummins et al., 2015), and oil futures markets (Dowling et al., 2016). There is also a significant literature on psychological retail pricing, which is used to take advantage of psychological barriers in consumers' minds; see, for example (Tifaoui and von Cramon-Taubadel, 2017), and the literature cited therein. In varying degrees, this literature provides general evidence in support of the presence of psychological price barriers.[4]

A dearth of prior behavioural investigation of coffee price barriers relates to the fact that the coffee price information typically available is that of the International Coffee Organization (ICO) indicator prices. These are price averages of similar coffee varieties or types, which means that they are not quotations of individual coffees.[5] We overcome this critical limitation by using price observations from proprietary databases owned by the ICO, which the organisation employs to compute its indicator prices. The salient feature of the data is that they refer to daily prices on the physicals market in the United States of seven coffee varieties of different quality and geographical origin. A further advantage of this database is that it spans more than two decades.

This rich data set enables us to contribute to the literature by answering a number of key research questions. First, is there evidence supporting the presence of psychological barriers centred at 00 in coffee prices? We analyse coffee prices expressed at the level of tens or hundreds digits. Second, to what extent does the presence of psychological price barriers vary across different coffee types? Third, to what extent are psychological price differential barriers present when we consider price differences between different coffee types? Fourth, weather anomalies or climate events such as El Niño and La Niña can cause extreme droughts or excess precipitation in coffee-producing regions, impacting on coffee growing conditions, production and ultimately prices.

With regard to the fourth contribution, we consider a question that has hitherto not been answered in the price barriers literature through asking whether knowledge of sea surface temperature anomalies related to El Niño and La Niña help predict the likelihood of the proximity of a coffee price to a specific barrier. To this end, we apply the novel one covariate at a time multiple testing (OCMT) approach to model selection proposed by Chudik et al. (2018), henceforth CKP. This is a regression-based variable selection algorithm that tests the statistical significance of each candidate variable individually and compared with other penalised regression methods[6] offers ease of interpretation, relation to classical statistical principles, validity under general assumptions (including dynamic extensions), computational speed, and superior performance in small samples.

The structure of the paper is as follows. The following section discusses in more detail the coffee price and climate data employed. The third section reports and discusses the evidence on coffee price barriers. We uncover evidence supporting the presence of

[3] We focus on price barriers such as 100 cents, 200 cents, etc., in the case of hundreds of cents, or 110 cents, 120 cents, etc., in the case of tens of cents.

[4] In the case of stock markets, the presence of psychological prices barriers points towards predictability thereby contradicting the efficient market hypothesis. There is also a large literature on psychological retail pricing.

[5] All the studies cited above but one use either yearly, quarterly or monthly versions of the four "indicator prices" of the ICO, which refer to composite prices of similar varieties: unwashed arabicas (primarily coffee from Brazil), Colombian milds (primarily coffee from Colombia), other milds (primarily coffee from other Latin American countries), and robusta (primarily coffee from African and Asian countries). The exception is Otero et al. (2018), who use weekly average and daily price data of eight coffee varieties from F.O. Licht's International Coffee Report. In this paper the terms "coffee variety" and "coffee type" are used interchangeably.

[6] Such as the least absolute shrinkage selection operator (LASSO) of Tibshirani (1996) and the Adaptive LASSO (A-LASSO) of Zou (2006), among others.

Table 1
Daily coffee prices (1 October 1998–21 January 2020).

Coffee	Type	Obs.	Mean	S.D.	Min.	Max.	C.V.
bra	$\mathcal{A}$	5,191	111.99	45.95	35.50	294.75	0.41
col	$\mathcal{A}$	5,191	142.24	54.79	57.50	331.50	0.39
gtm	$\mathcal{A}$	5,191	131.03	51.97	51.00	320.75	0.40
mex	$\mathcal{A}$	5,191	130.21	53.04	48.75	317.50	0.38
idn	$\mathcal{R}$	5,191	75.30	28.47	17.75	131.75	0.41
uga	$\mathcal{R}$	5,191	81.93	28.64	25.75	142.75	0.35
vnm	$\mathcal{R}$	5,191	73.60	27.85	15.75	130.75	0.38

Note: $\mathcal{A}$ and $\mathcal{R}$ indicate arabica and robusta, respectively. Prices are in US cents/lb. S.D. and C.V. indicate the standard deviation and the coefficient of variation, respectively. The source of the data is the International Coffee Organization.

psychological barriers in coffee prices at the level of hundreds digits, but not at the level of tens digits. There are clear differences when we divide our sample by quality. The fourth section considers the role of climate in price barrier proximity. We find a varied pattern of correlation between barrier proximity and (current and past) climate anomalies. The final section provides some concluding comments.

2. Data description

We use daily prices in US cents/lb, with two decimal points, on the physicals market in New York for the following seven varieties of coffee: Brazil Santos 3/4 screen size 14/16; Colombian Excelso UGQ screen size 14 (stands for Usual Good Quality); Guatemala Prime Washed; Mexico Prime Washed; Indonesia EK Grade 4 (stands for Eerste Kwaliteit in Dutch, that is First Quality); Uganda Standard; and Vietnam Grade 2.[7] Prices concern coffees of different origins traded in the New York market, so converting quotations from domestic currency units to US dollars is unnecessary, avoiding rounding issues related to exchange rates expressed with several significant digits. In addition, daily quotations data refer to trading in the late afternoon (New York time), which means that there is no need to look at trading rules that determine the minimum price change allowed in the market, nor to temporally aggregate intra-daily quotations. Lastly, daily price data come from at least five traders and brokers in the USA for each coffee variety mentioned above, suitably weighted by sales volume.[8]

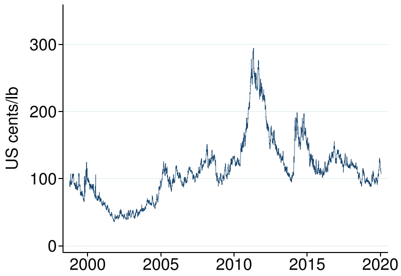
To simplify notation, in what follows we shall refer to these coffee varieties by their country of origin, which we sometimes abbreviate to three letters, that is `bra`, `col`, `gtm`, `mex`, `idn`, `uga`, and `vnm`, respectively. The first four varieties are arabica ($\mathcal{A}$) coffees, while the last three are robusta ($\mathcal{R}$) coffees. The study period runs from 1 October 1998 to 21 January 2020 for a total of $T = 5191$ time observations, excluding weekends and holidays (the approximate average number of days per year available for the empirical analysis is 244). During the study period, coffee production in these seven countries amounted to approximately 73% of total production by all coffee exporting countries. Additionally, in Brazil, Colombia, Guatemala, Mexico and Uganda there is participation of farmers in the country's coffee institutions, while in Indonesia and Vietnam this does not occur (see Coe, 2006).

Plots of the daily prices are presented in Fig. 1 for the arabica and robusta coffees. We refrain from presenting all seven prices in one plot to facilitate the visualisation of the individual series. As can be seen, the plots of the variables reveal a strong correlation within the arabica coffees, with a correlation coefficient of 0.98, and within the robusta coffees, with a correlation coefficient of 0.99. Table 1 presents some descriptive statistics of the price series at hand. The information contained in this table supports the idea that arabica coffees are typically viewed as of better quality compared to the robusta ones and therefore receive a quality premium. The more expensive coffees involve higher production costs driven by terrain quality, fertilisers, harvesting and processing methods, storage and transportation. Studies by Otero et al. (2018) and others find that the chemical composition of coffee beans affects prices, so producers need to be mindful about maintaining quality standards during the production process. Within the arabica group, Colombian coffee receives, on average, the highest quotations, followed by those from Guatemala and Mexico, all of which are processed using the washed method. Brazilian coffee, which is also an arabica but processed using the unwashed method, receives a lower average price. Price differences are somewhat smaller for the robusta coffees under consideration. Table 1 also reveals that the raw data arabica coefficients of variation (in the last column) are slightly higher than those for the robustas. We will see later that the relevance of price variability relates to the notion that psychological price barriers can be viewed as a source of rigidity not explained by economic fundamentals.

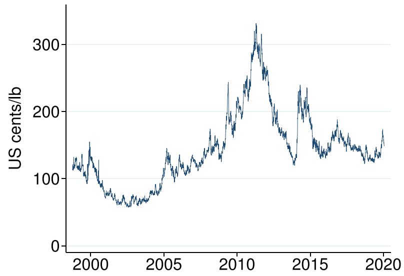
We also use daily climate data associated to the ocean component of the ENSO phenomenon. The idea here is to obtain a measure of sea surface temperature (SST) anomalies relative to a base period of thirty years; for our purposes, we estimate the measures of below- and above-normal SST using a slightly longer base period (that is, from 1 January 1990 to 21 November 2020). More

[7] The acronyms and numbers in the names refer to grading systems that define coffee standards in terms of limits on the size of the beans, number of defects and moisture percentage, among others. The interested reader is referred to the Food and Agriculture Organization (FAO) document "Grading and Classification of Green Coffee", downloaded from *www.ico.org*.

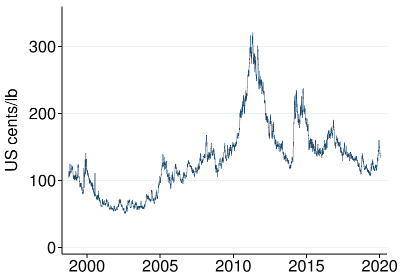
[8] One inevitable difficulty with the use of weighted averages across market participants is that there will be some rounding issues. We attempt to minimise these effects by focusing on psychological barriers at the levels of tens and hundreds digits. See International Coffee Organization (2011) for more details on the procedures followed to collect the price data.



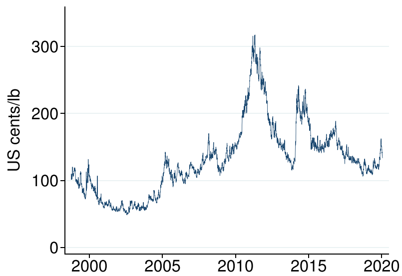
(a) Brazil ($\mathcal{A}$)



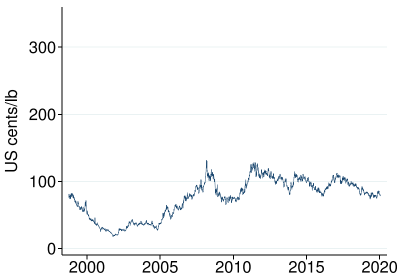
(b) Colombia ($\mathcal{A}$)



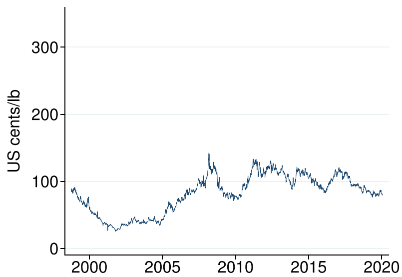
(c) Guatemala ($\mathcal{A}$)



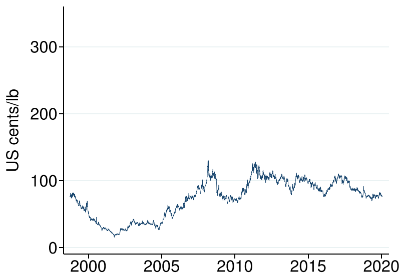
(d) Mexico ($\mathcal{A}$)



(e) Indonesia ($\mathcal{R}$)



(f) Uganda ($\mathcal{R}$)



(g) Vietnam ($\mathcal{R}$)

Fig. 1. Daily coffee prices (1 October 1998–21 January 2020).
Note: $\mathcal{A}$ and $\mathcal{R}$ indicate arabica and robusta, respectively. Prices are in US cents/lb. The source of the data is the International Coffee Organization.

specifically, we compute the area average SST from the El Niño 3.4 region at four locations on the Equator, namely 125, 140, 155 and 170 degrees west (longitude). From this, we then compute the average SST during the base period and subtract from the area averaged SST time series to obtain the SST anomalies. Finally, the resulting time series of anomalies is normalised by its

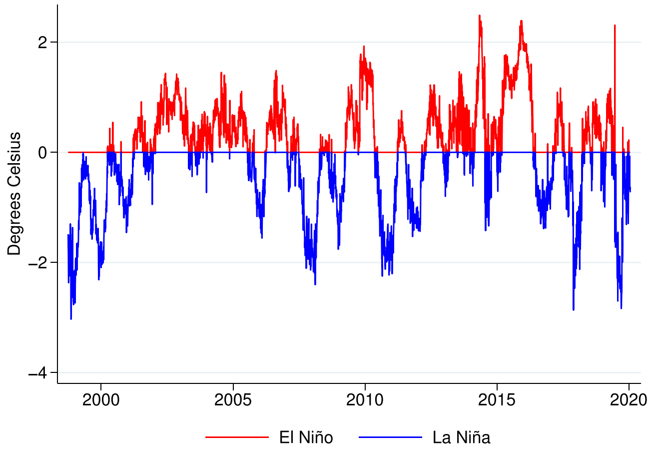


Fig. 2. Daily SST anomaly (1 October 1998–21 January 2020).
Note: The Sea Surface Temperature (SST) anomaly is a variable computed daily over the period from 1 October 1998 to 21 January 2020. The computation is relative to a longer thirty-year base period between 1 January 1990 and 21 November 2020. We compute the area average SST from the El Niño 3.4 region at four locations on the Equator line, namely 125, 140, 155, and 170 degrees west (longitude). The daily data series were downloaded on 11th April 2021 from https://www.pmel.noaa.gov/gtmba/.

standard deviation over the base period.[9] Climatologists subsequently smooth the anomalies with a five-month running mean. In this paper, however, we refrain from smoothing the anomalies data as such procedures induce in the series higher persistence and serial correlation in the form, by construction, of a moving average component. Thus, in the modelling exercise, there will be the need to address the latter either by adding MA lags or possibly approximating by adding AR lags. Neither is desirable, especially when it can be avoided altogether (see e.g., Wallis, 1974; Ghysels, 1990). The resulting time-series of SST anomalies is depicted in Fig. 2, where positive and negative values denote episodes of El Niño and La Niña, respectively.

3. Psychological price barriers

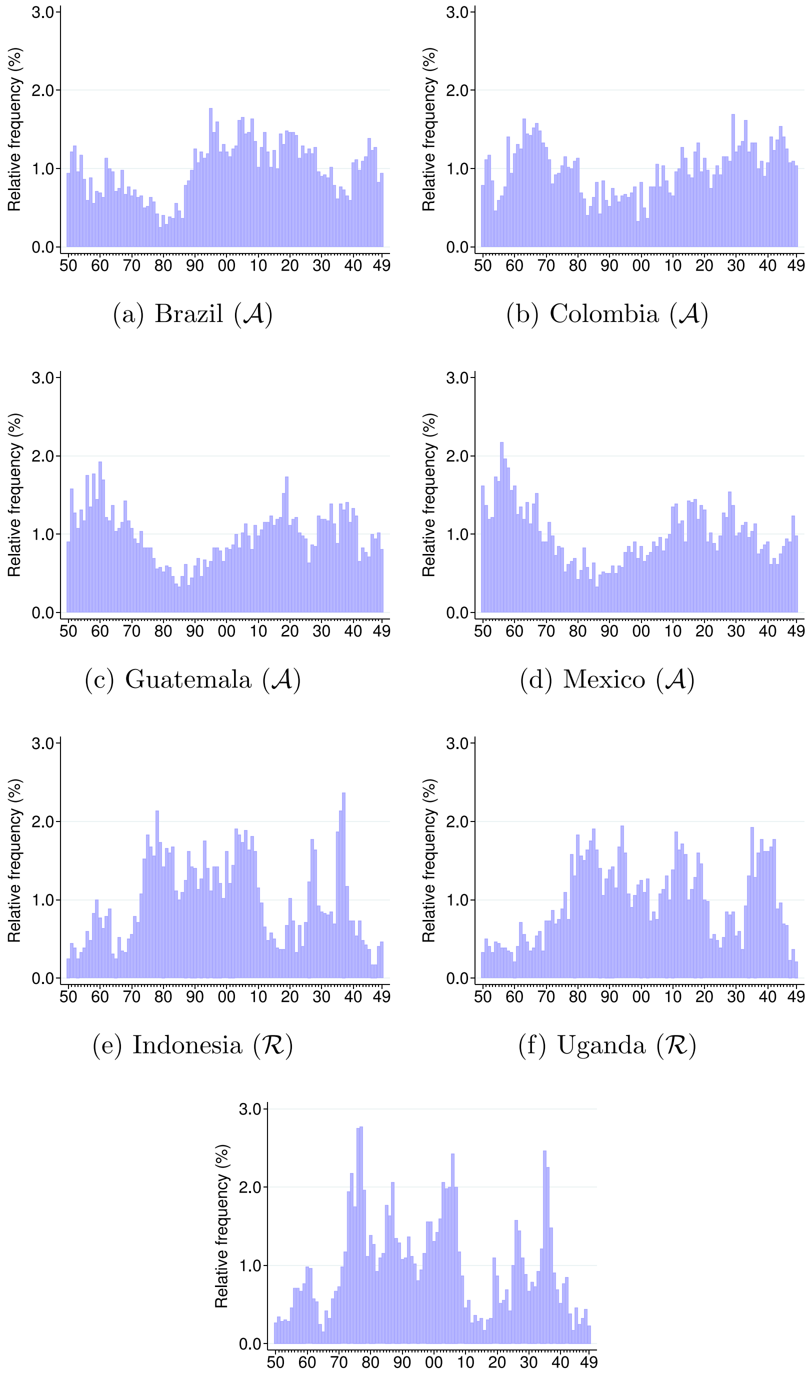
We commence our empirical analysis by observing that the smallest and largest values in the set of coffee prices are 15.75 and 331.50 US cents/lb, respectively (see Table 1). Given that all prices are below 1000, and following earlier literature, see for instance the analyses by Aggarwal and Lucey (2007) for gold and Dowling et al. (2016) for (WTI and Brent) crude oil futures markets, we shall test for the presence of psychological barriers at 100-levels and 10-levels in the underlying price series. We explore whether coffee price barriers are most likely to exist in terms of hundreds of cents of dollars around 00 price digits, such as 100 cents, 200 cents, etc. Similarly, there is the possibility that price barriers are most likely to exist in terms of tens of cents of dollars around 00 price digits, such as 110 cents, 120 cents, etc. Either way, one might initially consider the possibility of a higher frequency of 00 digits compared to other digits.[10]

In order to investigate the frequency of digits, we decompose the coffee price series such that every observed price is expressed as a two-digit representation. The hundreds digits are the pair of digits before the decimal point, that is oXX.oo, while the tens digits are the pair of digits before and after the decimal point, that is ooX.Xo.[11] To illustrate these ideas, let us consider the sequence of prices 88.50, 101.00, and 120.25. In the hundreds digits we would extract 88, 01, and 20, while in the tens digits the corresponding numbers would be 85, 10, and 02. As indicated, for instance, by Donaldson and Kim (1993) and De Ceuster et al. (1998), all the hundreds and tens digits are in the set $\{00, 01, \ldots, 98, 99\}$ and are cyclical.

[9] El Niño region 3.4 lies between latitude coordinates 5N-5S and longitude coordinates 170W-120 W. The data that we have available measures SST at midday. The source of the data is the Pacific Marine Environmental Laboratory National, part of the National Oceanic and Atmospheric Administration (NOAA) of the United States Department of Commerce. The data series were downloaded on 11 April 2021 from https://www.pmel.noaa.gov/gtmba/. We do not download the 1950-present SST data directly from NOAA because that information is available as a three-month running mean, and we require it on a daily frequency for the purpose of our econometric modelling exercise.

[10] We focus on barriers at 00-centred levels since they are the ones that receive attention from economic and financial analysts, sometimes incited by the media. However, there may well be structural reasons or other institutional factors across all markets, related to trading costs or transaction costs, behind barriers at different price points. In addition, throughout human history, religious and sociological reasons have granted importance to other numerical values. For example, the number 40 has special meaning in Christianity and Islam; see Mitchell (2001) for an overview of the literature on symbolic numbers, clustering, and psychological barriers.

[11] We do not study the ones digits, that is the pair of numbers to the right of the decimal point, as they are less interesting from an economic point of view.



(a) Brazil ($\mathcal{A}$)

(b) Colombia ($\mathcal{A}$)

(c) Guatemala ($\mathcal{A}$)

(d) Mexico ($\mathcal{A}$)

(e) Indonesia ($\mathcal{R}$)

(f) Uganda ($\mathcal{R}$)

(g) Vietnam ($\mathcal{R}$)

Fig. 3. Relative frequency of hundreds of US cents around 00 price digits.

Table 2
Pearson's χ^2 uniformity test.

Coffee	Type	Hundreds digits		Tens digits	
		χ^2	p-value	χ^2	p-value
Price levels					
bra	$\mathcal{A}$	633.2	[0.000]	43.9	[0.271]
col	$\mathcal{A}$	512.5	[0.000]	43.0	[0.303]
gtm	$\mathcal{A}$	581.6	[0.000]	4388.9	[0.000]
mex	$\mathcal{A}$	695.4	[0.000]	4385.2	[0.000]
idn	$\mathcal{R}$	1552.1	[0.000]	353.2	[0.000]
uga	$\mathcal{R}$	1278.6	[0.000]	296.4	[0.000]
vnm	$\mathcal{R}$	2052.2	[0.000]	441.3	[0.000]
Absolute price differentials					
bra-col	$\mathcal{A}-\mathcal{A}$	9224.8	[0.000]	3151.9	[0.000]
bra-gtm	$\mathcal{A}-\mathcal{A}$	4397.4	[0.000]	9255.0	[0.000]
bra-mex	$\mathcal{A}-\mathcal{A}$	4239.6	[0.000]	6574.7	[0.000]
bra-idn	$\mathcal{A}-\mathcal{R}$	5341.1	[0.000]	195.0	[0.000]
bra-uga	$\mathcal{A}-\mathcal{R}$	6434.7	[0.000]	177.0	[0.000]
bra-vnm	$\mathcal{A}-\mathcal{R}$	5445.7	[0.000]	191.8	[0.000]
col-gtm	$\mathcal{A}-\mathcal{A}$	10732.2	[0.000]	8440.1	[0.000]
col-mex	$\mathcal{A}-\mathcal{A}$	9204.7	[0.000]	6215.0	[0.000]
col-idn	$\mathcal{A}-\mathcal{R}$	4595.2	[0.000]	178.3	[0.000]
col-uga	$\mathcal{A}-\mathcal{R}$	4092.2	[0.000]	176.9	[0.000]
col-vnm	$\mathcal{A}-\mathcal{R}$	4153.6	[0.000]	162.9	[0.000]
gtm-mex	$\mathcal{A}-\mathcal{A}$	106.7	[0.000]	10791.6	[0.000]
gtm-idn	$\mathcal{A}-\mathcal{R}$	4956.1	[0.000]	4407.4	[0.000]
gtm-uga	$\mathcal{A}-\mathcal{R}$	4486.9	[0.000]	4300.2	[0.000]
gtm-vnm	$\mathcal{A}-\mathcal{R}$	4546.6	[0.000]	4617.6	[0.000]
mex-idn	$\mathcal{A}-\mathcal{R}$	4622.0	[0.000]	4361.6	[0.000]
mex-uga	$\mathcal{A}-\mathcal{R}$	4326.8	[0.000]	4609.9	[0.000]
mex-vnm	$\mathcal{A}-\mathcal{R}$	4519.9	[0.000]	4381.4	[0.000]
idn-uga	$\mathcal{R}-\mathcal{R}$	249.8	[0.000]	7332.9	[0.000]
idn-vnm	$\mathcal{R}-\mathcal{R}$	1.0	[0.327]	12676.0	[0.000]
uga-vnm	$\mathcal{R}-\mathcal{R}$	2236.1	[0.000]	8339.9	[0.000]

Note: $\mathcal{A}$ and $\mathcal{R}$ indicate arabica and robusta, respectively.

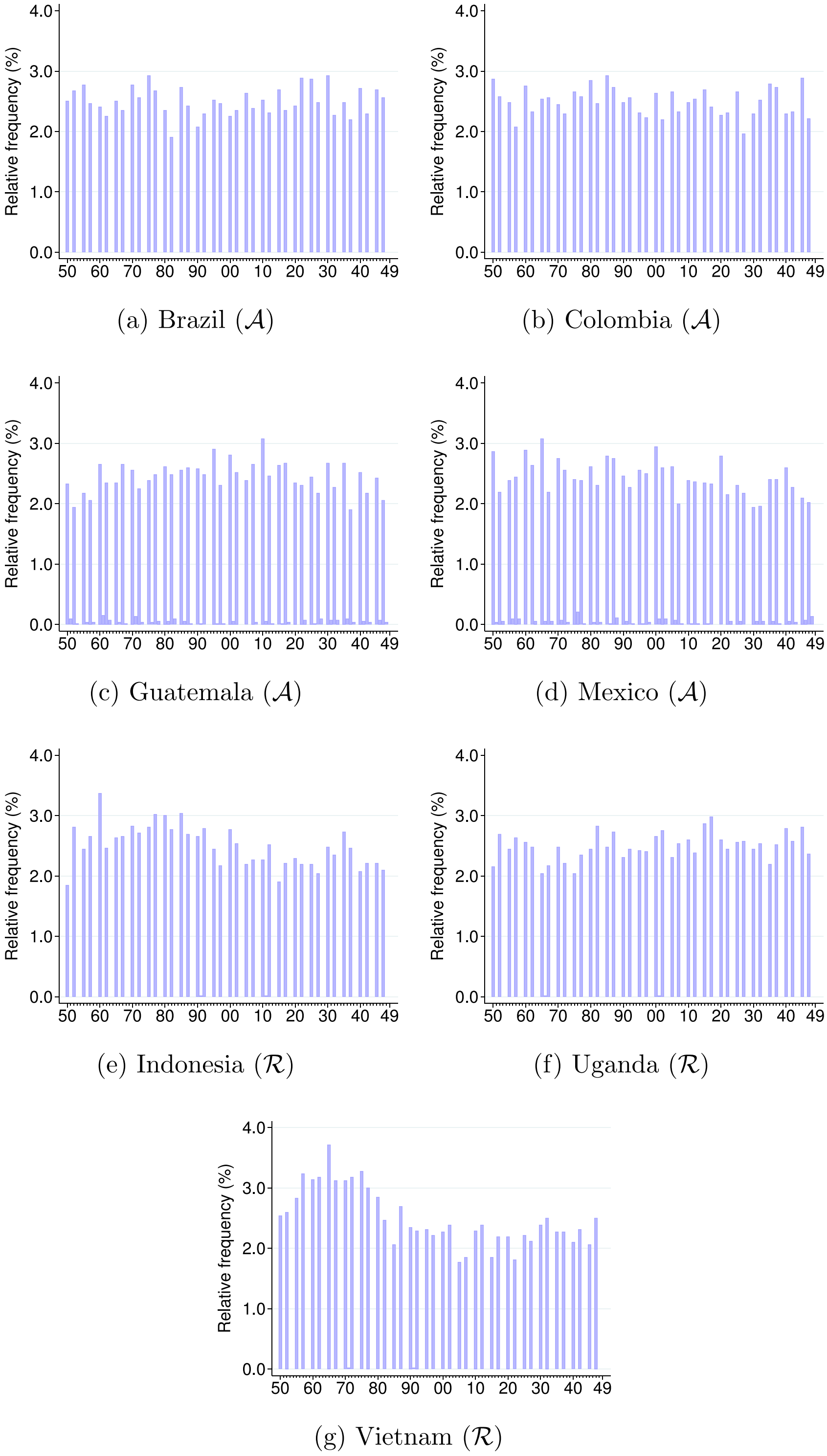
Figs. 3 and 4 display the relative frequencies of the hundreds and tens of US cents around 00 price digits for the prices of the arabica and robusta coffees, respectively.[12] As in De Ceuster et al. (1998), we highlight the cyclical nature of the hundreds and tens digits by constructing these figures in a way such that in the horizontal axis the digits 00 are plotted at the centre. Visual inspection of these figures indicates that the tens digits exhibit more gaps and the height of the bars is somewhat similar. As for the hundreds digits figures, there are a few more humps which denote an increasing relative frequency of occurrence. While there is mixed evidence of a higher frequency of 00 digits compared to other digits, these graphical findings provide initial support for psychological price barriers in hundreds digits. Moreover, a further examination of Fig. 3 also reveals that for bra, col, gtm and mex, there is a dip in the hundreds relative frequencies attached to digits in the proximity and to the left of 00.

In terms of changes in price behaviour, a possibility here is that there is a certain barrier around a 00 digit price that defines the closeness of a traded price. For the remaining robusta coffees, the relative frequencies attached to digits in the proximity of 00 are greater than for the arabica coffees. The plots in Appendices A and B respectively display the relative frequencies of the hundreds and tens digits for the twenty-one absolute price differentials which can be computed among the seven coffee prices under examination. In all cases, the 00 digit has a very low frequency. For many of the hundreds cases, there is visual evidence of negative clustering away from a wide barrier around 00. Indeed, this clustering is often strongly skewed above 00. Such clustering might be consistent with a stronger resistance to downward rather than upward breaches of a price barrier. We now apply a number of statistical procedures most commonly used to formally test for the presence of psychological barriers in coffee prices.

3.1. Uniformity test

We begin by assessing whether or not the digits that can be extracted from the price data are all equally likely using Pearson's χ^2 uniformity test. The underlying idea is that departures from uniformity in the relative frequency of (in our case, hundreds and tens) digits can be interpreted as evidence in favour of the presence of coffee price anomalies. The results reported in Table 2 indicate

[12] Since the extracted series of hundreds and tens are bounded between 00 and 99, one would expect to reject non-stationarity, and this was confirmed in earlier results (available on request) using the ADF and ADF_{max} unit root tests of Dickey and Fuller (1979) and Leybourne (1995), respectively. This finding rules out a cointegration analysis based on the extracted series alone. Another possibility is testing cointegration relationships between the actual data conditioned by thresholds based on the extracted data. In other words, the question is, if one or other of the two series are in the vicinity of a barrier, what might be the impact on their relationship? Although this question is of interest, we leave this to future research.



(a) Brazil ($\mathcal{A}$)

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(f) Uganda ($\mathcal{R}$)

(g) Vietnam ($\mathcal{R}$)

Fig. 4. Relative frequency of tens of US cents around 00 price digits.

Table 3
Proximity test for hundreds and tens digits.

	$d_{00,00}$		$d_{98,02}$		$d_{95,05}$		$d_{90,10}$	
	Hundreds	Tens	Hundreds	Tens	Hundreds	Tens	Hundreds	Tens
	α_1	α_1	α_1	α_1	α_1	α_1	α_1	α_1
Price levels								
bra	11.2	65.7	12.5	−4.3	24.1***	6.5	23.0***	1.6
col	−9.0	85.9	−24.1***	−1.8	−19.1***	5.5	−20.1***	2.8
gtm	−9.0	95.0	−11.5	4.5	−10.0*	10.8	−12.1***	9.1
mex	−8.0	102.1	−12.7	7.5	−12.0**	13.2	−13.9***	5.6
idn	32.4	93.0	16.5	3.5	26.3***	6.0	31.4***	3.6
uga	13.2	87.0	9.6	4.7	4.2	8.4	13.4**	4.6
vnm	16.3	66.8	26.8*	−3.7	28.7***	−0.2	25.1***	−3.9
Absolute price differentials								
bra-col	−49.4	226.4**	−52.3	9.8	−56.0**	−4.2	−60.5***	3.9
bra-gtm	−42.5	58.7	−44.3	−19.1	−47.3**	27.6	−37.4**	7.6
bra-mex	−38.4	47.6	−40.1	−16.3	−42.8**	22.6	−29.8*	8.3
bra-idn	−51.1	48.6	−52.2**	−10.0	−55.0***	−0.6	−58.6***	−3.1
bra-uga	−41.8	67.8	−43.5*	−4.7	−46.5***	4.9	−42.1***	1.9
bra-vnm	−49.4	54.6	−51.0**	−3.7	−54.6***	3.3	−59.4***	2.0
col-gtm	−25.1	52.6	−26.1	−17.0	−27.9	−0.8	−10.8	−14.1
col-mex	−28.5	32.4	−29.7	−15.5	−31.6	−1.2	−22.9	−17.1
col-idn	−30.2	84.9	−37.6*	−7.5	−40.5***	3.7	−46.7***	2.4
col-uga	−35.3	90.0	−41.0*	0.5	−45.6***	5.9	−50.1***	1.5
col-vnm	−36.3	67.8	−37.6*	−3.3	−42.1***	2.6	−46.8***	2.1
gtm-mex	−1.2	193.0*	−1.2	83.5*	−1.3	49.0	3.1	54.7**
gtm-idn	−33.2	76.9	−42.2*	−2.9	−46.6***	3.6	−54.3***	0.1
gtm-uga	−49.3	90.0	−49.1**	8.7	−50.8***	13.9	−55.2***	11.4
gtm-vnm	−40.3	76.9	−43.1*	0.1	−46.8***	4.0	−52.7***	0.7
mex-idn	−44.4	60.7	−41.4*	−8.7	−45.3***	1.9	−52.7***	−0.6
mex-uga	−45.2	97.1	−48.1**	8.7	−50.5***	15.9	−53.4***	11.9
mex-vnm	−42.3	62.7	−43.7**	−2.6	−45.3***	1.2	−51.0***	−1.5
idn-uga	−6.4	167.8	−6.7	−8.3	−7.2	−15.3	3.9	9.3
idn-vnm	−0.5	610.2***	−0.5	118.0	−0.6	103.9*	0.7	123.9***
uga-vnm	−15.0	372.8***	−15.6	42.8	−16.7	16.6	15.9	32.1

Note: The regression is $F(M) = \alpha_0 + \alpha_1 d_{i,j} + \varepsilon_M$; $M = 00, 01, \ldots, 99$, where $F(M)$ is the absolute frequency of hundreds (or tens) digits; see equation (1). All regressions are estimated using 100 observations. In the hundreds regressions the coefficient of determination, R^2, varies between 0.00 and 0.27, with an average of 0.06. In the tens regressions it varies between 0.00 and 0.11, with an average of 0.01. Intercept and R^2 are not reported for brevity.

***Statistical Significance: $p < 0.01$.

**Statistical Significance: $p < 0.05$.

*Statistical Significance: $p < 0.10$.

that except for bra and col tens series, there is evidence that the hundreds and tens series are not uniformly distributed. Similarly, except for idn-vnm, there is evidence of anomalies across all absolute price differentials.

This initial finding of coffee price anomalies points to the possibility that coffee market pricing is subject to psychological factors. Indeed, this might be a reflection of coffee traders' relative willingness to transact over certain prices. De Ceuster et al. (1998), however, drawing on Benford (1938) law of anomalous numbers, show that even when there are no psychological barriers the relative frequency of the digits need not resemble a uniform distribution. If such a rejection of uniformity is not in itself sufficient to demonstrate the existence of coffee price barriers, we next examine the frequency and distribution of the digits values at and near a range of hypothesised 00-centred barriers. With a focus on price barriers, this will further extend the new insights into coffee market behaviour.

3.2. Barrier tests

In this section, we conduct two types of barrier tests. The barrier proximity test is for negative clustering at the price barrier, while the barrier hump test is for a persistent barrier. Both these tests involve a range of pre-supposed barriers that are 00-centred. The barrier proximity test is based on the following regression:

$$F(M) = \alpha_0 + \alpha_1 d_{i,j} + \varepsilon_M; \qquad M = 00, 01, \ldots, 99, \tag{1}$$

where $F(M)$ is the absolute frequency with which a price lies with its hundreds (or tens) digits in cell M; $d_{i,j}$ is a dummy variable that measures the length of the price barrier in the range from i to j in the neighbourhood around $M = 00$, with $\{i, j\}$ defined over the intervals $\{00\}$, $\{98, 99, 00, 01, 02\}$, $\{95, \ldots, 00, \ldots, 05\}$, and $\{90, \ldots, 00, \ldots, 10\}$; ε_M is the error term. To understand the rationale behind the test intuitively, notice that when $\alpha_1 = 0$ Eq. (1) becomes a regression of the absolute frequency of (hundreds or tens) digits against an intercept, providing support for the absence of barriers. In turn, $\alpha_1 > 0$ ($\alpha_1 < 0$) indicates an upward (downward) shift at the hypothesised barrier, meaning higher absolute frequencies of digits inside (outside) the hypothesised barrier at $d_{i,j}$.

Table 4
Barrier hump test for hundreds and tens digits.

	Hundreds digits regressions			Tens digits regressions		
	β_1	β_2	R^2	β_1	β_2	R^2
Price levels						
bra	−1.27***	0.01***	0.38	0.08	0.00	0.00
col	1.20***	−0.01***	0.42	−0.01	0.00	0.00
gtm	0.84***	−0.01***	0.39	−0.38	0.00	0.00
mex	0.93***	−0.01***	0.30	−0.14	0.00	0.00
idn	−1.86***	0.02***	0.27	0.03	0.00	0.00
uga	−1.51***	0.02***	0.21	−0.19	0.00	0.00
vnm	−1.58***	0.02***	0.18	0.63	−0.01	0.01
Absolute price differentials						
bra-col	0.31	−0.02*	0.27	0.52	−0.01	0.00
bra-gtm	−1.88**	0.00	0.31	−0.39	0.00	0.00
bra-mex	−1.60**	0.00	0.29	−0.54	0.00	0.00
bra-idn	1.10*	−0.02***	0.42	0.41	−0.01	0.00
bra-uga	−0.29	−0.01	0.38	0.05	0.00	0.00
bra-vnm	1.62***	−0.03***	0.42	0.15	0.00	0.00
col-gtm	−2.15***	0.01	0.21	1.16	−0.01	0.02
col-mex	−2.04***	0.01	0.23	1.19	−0.01	0.02
col-idn	4.69***	−0.05***	0.51	0.13	0.00	0.00
col-uga	4.28***	−0.05***	0.56	0.11	0.00	0.00
col-vnm	4.69***	−0.05***	0.56	0.11	0.00	0.00
gtm-mex	−0.19*	0.00	0.06	−4.38***	0.03**	0.22
gtm-idn	4.24***	−0.05***	0.47	0.29	0.00	0.00
gtm-uga	3.06***	−0.04***	0.45	−0.59	0.01	0.01
gtm-vnm	4.39***	−0.05***	0.51	0.19	0.00	0.00
mex-idn	3.72***	−0.04***	0.42	0.21	0.00	0.00
mex-uga	2.43***	−0.03***	0.40	−0.36	0.00	0.00
mex-vnm	3.92***	−0.04***	0.44	0.29	0.00	0.00
idn-uga	−0.99**	0.01*	0.11	0.44	0.00	0.01
idn-vnm	−0.09*	0.00	0.05	−7.33***	0.05**	0.15
uga-vnm	−2.29**	0.02*	0.10	−0.73	0.01	0.01

Note: The regression is $F(M) = \beta_0 + \beta_1 M + \beta_2 M^2 + \epsilon_M$; $M = 00, 01, \dots, 99$, where $F(M)$ is the absolute frequency of hundreds (or tens) digits; see equation (2). Intercept not reported to save space. All regressions are estimated using 100 observations. R^2 denotes the coefficient of determination.
***Statistical Significance: $p < 0.01$.
**Statistical Significance: $p < 0.05$.
*Statistical Significance: $p < 0.10$.

In Table 3, we are unable to reject the no-barriers hypothesis for the tens digits throughout. In the case of the hundreds digits, the no-barriers null is rejected more often as the barriers become wider. At the widest 90–10 barrier, the null is rejected throughout at the 1% significance level or better in the cases of col, gtm and mex where the negative estimate for α_1 suggests that the presence of barriers will result in a lower frequency of M-values or negative clustering at the barrier. According to Table 1, these three coffees are of the greatest quality and are the most expensive on average. As indicated in Fig. 3, for these coffees the minimum relative frequency is more proximate towards 00 than is the case for the other cheaper bra, idn, uga and vnm coffees.

If we examine the absolute price differentials, then as with the earlier results, evidence of negative clustering at the barrier is restricted to the hundreds digits. In contrast to the earlier results, there is more extensive evidence of negative clustering particularly at the widest two barriers. Moreover, negative clustering appears to be present when we consider differentials involving arabica bra, col, gtm or mex minus robusta idn, uga or vnm. These results suggest that if psychological price barriers are a characteristic of arabica coffee pricing, then this is indirect in the sense of working through price differentials.

The barrier hump test involves a regression of the absolute frequency defined above, $F(M)$, against the M values themselves and their squares M^2, that is:

$$F(M) = \beta_0 + \beta_1 M + \beta_2 M^2 + \epsilon_M; \qquad M = 00, 01, \dots, 99, \tag{2}$$

where ϵ_M is the error term. For this test, the underlying idea is that the sign of the coefficient associated with M^2 indicates barrier persistence based on the entire shape of the empirical distribution of M-values. More specifically, the null hypothesis that there is no barrier is $\beta_2 = 0$. At the same time, under the alternative, one can find that $\beta_2 > 0$, revealing a U-shaped relationship where the mass of absolute frequencies is greater nearer the extremes of the M values, or that $\beta_2 < 0$, suggesting an inverted U-shaped relationship such that the mass of frequencies is greater away from the extreme values of M.

The barrier hump tests are reported in Table 4. The null of no-barriers should result in β_2 being zero, while under the alternative of barriers it will be expected to be negative and significant. In the case of the tens digits, all the β_2 estimates are insignificant. For the hundreds digits, the estimates for β_2 are significant throughout at the 1% level. This is evidence of a persistent barrier in the cases of col, gtm and mex for which β_2 is both significant and negative. For the coffee price differentials, β_2 is both negative

Table 5
Tests of conditional effects: Hundreds digits.

RW (k)	Regressors	Coffee variety						
		`bra`	`col`	`gtm`	`mex`	`idn`	`uga`	`vnm`
(1)	BDB_t	1.37***	−0.23	−0.29	0.20	0.18	−0.10	0.48
	BUB_t	0.70*	−0.05	0.23	−0.02	0.10	0.16	0.77*
	ADB_t	−1.29***	−0.09	−0.75**	−0.66*	−0.73	0.55	−0.54
	AUB_t	−0.35	−0.48	−0.24	0.36	−1.48***	1.02*	−0.26
(2)	BDB_t	1.02***	−0.48*	0.00	0.26	0.30	0.06	0.54*
	BUB_t	0.03	0.02	−0.21	0.11	0.12	−0.09	0.36
	ADB_t	−0.53*	0.04	−0.29	−0.53**	0.21	0.25	0.04
	AUB_t	−0.55*	0.00	−0.25	−0.13	−0.98***	0.29	−0.45
(3)	BDB_t	0.51**	−0.43**	0.18	0.21	0.26	−0.05	0.41*
	BUB_t	0.29	−0.04	−0.15	0.20	−0.20	0.26	0.37
	ADB_t	−0.52**	0.17	−0.30	−0.42**	0.28	0.17	−0.24
	AUB_t	−0.30	−0.20	−0.04	0.02	−0.63**	−0.20	−0.05
(4)	BDB_t	0.68***	−0.11	0.16	0.34*	0.18	−0.20	0.27
	BUB_t	0.15	−0.15	−0.27	−0.07	−0.06	0.39	0.20
	ADB_t	−0.39*	0.04	−0.03	−0.24	0.21	0.05	−0.21
	AUB_t	−0.39*	0.11	0.08	0.14	−0.47*	0.03	−0.02
(5)	BDB_t	0.67***	−0.11	0.24	0.36**	0.16	−0.10	0.14
	BUB_t	0.08	−0.10	−0.16	−0.10	0.00	0.18	0.12
	ADB_t	−0.32*	0.04	0.22	−0.04	0.31	0.22	−0.16
	AUB_t	−0.32*	0.31*	0.02	0.03	−0.35	−0.03	0.06
(10)	BDB_t	0.45***	0.02	0.19	0.18	0.13	−0.07	0.05
	BUB_t	−0.05	0.00	−0.15	0.11	−0.02	0.18	0.01
	ADB_t	−0.01	−0.04	0.20	−0.05	−0.01	0.13	−0.02
	AUB_t	−0.28*	0.11	−0.02	−0.05	−0.18	−0.18	−0.08

Note: The regression is $r_t = \phi_0 + \phi_1 BDB_t^{(k)} + \phi_2 BUB_t^{(k)} + \phi_3 ADB_t^{(k)} + \phi_4 AUB_t^{(k)} + \phi_5 r_{t-1} + \eta_t$, where r_t is the one-day return; see equation (3). The estimates of ϕ_0 and ϕ_5 are not reported to save space. RW is the reaction window (in days) to assess the speed of market reaction before (B) and after (A) a downward (D) or upward (U) breach. BDB_t, BUB_t, ADB_t and AUB_t are dummy variables defined accordingly.
***Statistical Significance: $p < 0.01$.
**Statistical Significance: $p < 0.05$.
*Statistical Significance: $p < 0.10$.

and significant when we consider the hundreds differentials involving arabica `bra`, `col`, `gtm` and `mex` minus robusta `idn`, `uga` or `vnm`.[13]

In furthering our understanding of the coffee market, these barrier test results suggest that there is some evidence that the coffee market is characterised by the presence psychological price barriers for both price levels and absolute price differentials. The barrier proximity tests suggest that this is more often the case for the hundreds digits with the wider barriers around 00-centred prices. Most of these cases demonstrate negative clustering outside of the barrier. The barrier hump test results provide further support for negative clustering. The arabica coffees are mostly characterised by an inverted U-shaped relationship such that the mass of frequencies is greater away from the extremes of the M-values. For the less expensive robusta coffees, the impact of psychological price barriers is perhaps more of an indirect nature insofar as only applying to coffee price differentials.

3.3. Tests of conditional effects

The evidence so far suggests that `col`, `gtm` and `mex` hundreds digits are characterised by negative clustering at a wide barrier that surrounds 00. We now investigate whether the dynamics of coffee price returns differ before and after breaches of the hypothesised barriers. As in Aggarwal and Lucey (2007), Cummins et al. (2015), Dowling et al. (2016), and Berk et al. (2017), among others, we estimate the following regression:

$$r_t = \phi_0 + \phi_1 BDB_t^{(k)} + \phi_2 BUB_t^{(k)} + \phi_3 ADB_t^{(k)} + \phi_4 AUB_t^{(k)} + \phi_5 r_{t-1} + \eta_t, \quad (3)$$

where r_t is the one-day return, calculated as the log-price difference adjusted by the number of trading dates between t and $t-1$, multiplied by 100; $BDB_t^{(k)}$ is an indicator variable which assigns the value of 1 to the k days Before a Downward Breach from

[13] To assess the robustness of our findings, we also considered standard errors based on clustering followed by the estimation of panel versions of Eqs. (1) and (2). Standard errors based on clustering led to results that are qualitatively similar. The panel findings supported the view that there are commonalities in humps and barriers and confirmed the insights obtained from when the tests were applied to the individual series. These results are available on request.

Table 6
Tests of conditional effects: Tens digits.

RW (k)	Regressors	Coffee variety						
		bra	col	gtm	mex	idn	uga	vnm
(1)	BDB_t	−0.02	0.24***	0.11	0.21**	0.19	0.01	0.08
	BUB_t	0.26**	0.15*	−0.02	0.02	0.14	0.03	0.25**
	ADB_t	−0.15	−0.10	−0.09	0.04	0.03	0.10	0.02
	AUB_t	0.15	−0.14	0.12	0.08	−0.19	0.02	−0.25**
(2)	BDB_t	0.06	0.27***	0.09	0.18**	0.10	0.02	0.05
	BUB_t	0.13	0.08	0.09	0.04	0.07	−0.06	0.15
	ADB_t	−0.16*	−0.08	−0.04	0.00	0.18**	0.04	0.20**
	AUB_t	0.00	−0.16**	−0.02	−0.04	−0.14	−0.01	−0.18**
(3)	BDB_t	0.03	0.20***	0.06	0.09	0.05	−0.02	0.14*
	BUB_t	0.12	0.06	0.05	0.06	0.06	0.00	0.06
	ADB_t	−0.14*	−0.10*	−0.01	−0.03	0.13*	0.08	0.14*
	AUB_t	−0.08	−0.09	−0.04	0.02	−0.10	−0.09	−0.07
(4)	BDB_t	0.09	0.14***	0.09	0.09	0.03	−0.02	0.09
	BUB_t	0.13*	0.05	−0.02	0.02	0.00	−0.03	0.01
	ADB_t	−0.11	−0.09*	−0.01	0.00	0.11*	0.08	0.15**
	AUB_t	−0.09	0.01	−0.03	−0.03	−0.07	−0.03	−0.11
(5)	BDB_t	0.12*	0.16***	0.10*	0.08	0.08	0.00	0.03
	BUB_t	0.09	−0.01	−0.03	−0.01	−0.04	−0.06	0.01
	ADB_t	−0.07	−0.07	0.02	−0.03	0.07	0.08	0.09
	AUB_t	−0.07	0.01	−0.05	0.01	−0.03	−0.02	−0.06
(10)	BDB_t	0.07	0.20***	0.13**	0.05	0.09	0.06	0.10*
	BUB_t	0.02	−0.01	−0.02	0.00	−0.04	−0.08	0.00
	ADB_t	0.04	−0.05	0.05	0.06	0.06	0.09*	0.10*
	AUB_t	−0.06	−0.08*	−0.08	−0.09	−0.12**	−0.06	−0.16***

Note: The regression is $r_t = \phi_0 + \phi_1 BDB_t^{(k)} + \phi_2 BUB_t^{(k)} + \phi_3 ADB_t^{(k)} + \phi_4 AUB_t^{(k)} + \phi_5 r_{t-1} + \eta_t$, where r_t is the one-day return; see equation (3). The estimates of ϕ_0 and ϕ_5 are not reported to save space. RW is the reaction window (in days) to assess the speed of market reaction before (B) and after (A) a downward (D) or upward (U) breach. BDB_t, BUB_t, ADB_t and AUB_t are dummy variables defined accordingly.
***Statistical Significance: $p < 0.01$.
**Statistical Significance: $p < 0.05$.
*Statistical Significance: $p < 0.10$.

above because of decreasing prices; $BUB_t^{(k)}$ is an indicator variable which assigns the value of 1 to the k days Before an Upward Breach from below because of increasing prices; $ADB_t^{(k)}$ is an indicator variable which assigns the value of 1 to the k days After a Downward Breach from above because of decreasing prices; and $AUB_t^{(k)}$ is an indicator variable which assigns the value of 1 to the k days After an Upward Breach from below because of increasing prices. The error term is η_t. The coefficients ϕ_1, ϕ_2, ϕ_3, and ϕ_4 can reveal potentially differentiated returns before and after breaches of the hypothesised barriers, either from above or below.

Tables 5 and 6 summarise the results of the conditional effects tests, where the reaction window to assess the speed of market reaction before and after a downward or upward breach is set equal to $k = 1, 2, 3, 4, 5, 10$ days. If we look at Table 5, then out of 16 cases of significance (at the 5% level) for the hundreds digits, 9 are negative. The coefficients on $ADB_t^{(k)}$ are generally negative when significant reflecting a further lower movement in prices once the barrier is breached. This is particularly the case for `bra` and `mex`. The role of $AUB_t^{(k)}$ is negative when significant in the case of `idn` reflecting market resistance to further upward movements in prices. $BDB_t^{(k)}$ tends to exert a positive effect when significant thereby reflecting a resistance to prices falling below a barrier, particularly for `bra`. In the case of the results for the tens digits reported in Table 6, 5 out of 19 significant cases (at the 5% level) are negative. The coefficients on $BDB_t^{(k)}$ tend to be positive when significant, most notably this time for `col` and `mex`. The impact from $ADB_t^{(k)}$ is positive when significant reflecting less lower movement in prices once the barrier is breached. This is particularly the case for `idn` and `vnm`.

4. Psychological price barriers and climate

We have so far uncovered two key findings. First, there is a significant presence of negative clustering at psychological price barriers in the cases of the highest quality coffees. Second, for coffees in general, there is evidence of a change in the dynamics of price returns before and after any barrier breaches that might occur. In further exploring the presence of psychological coffee price barriers, we now assess if there is evidence that climate impacts significantly on the likelihood of coffee prices being in the proximity of a psychological 00 price. This analysis builds upon earlier studies such as Ubilava (2012), and Sephton (2019) that have confirmed the impact of El Niño and La Niña on world coffee prices.

Drawing on the discussion of barrier tests in Section 3.2, let $d_{i,j,t}$ be a dummy time-series variable that measures the length of the price barrier in the range from i to j in the neighbourhood around $M = 00$ at time t, with $\{i, j\}$ defined over the intervals $\{00\}$, $\{98, 99, 00, 01, 02\}$, $\{95, \ldots, 00, \ldots, 05\}$, and $\{90, \ldots, 00, \ldots, 10\}$.[14] The dummy variable $d_{i,j,t}$ is intended to capture the notion of being in the "proximity" of the 00 barrier, where proximity is understood to vary from being exactly at the 00 barrier, $d_{00,00,t}$, to the more ample 90–10 barrier, $d_{90,10,t}$. The specific regression model we have in mind for each of the seven coffee varieties is:

$$d_{i,j,t} = \gamma_0 + \gamma_1 d_{i,j,t-1} + \sum_{i=0}^{n} \gamma_{1i} sst_{t-i}^{(+)} + \sum_{i=0}^{n} \gamma_{2i} sst_{t-i}^{(-)} + v_t, \tag{4}$$

where, in addition to the dependent variable already defined ($d_{i,j,t}$) and its first lag ($d_{i,j,t-1}$), $sst_{t-i}^{(+)}$ and $sst_{t-i}^{(-)}$ are current ($i = 0$) and past ($i > 0$) values of positive and negative SST deviations in relation to a 30-year base period, respectively.[15] The error term is v_t.

Our goal is to predict $d_{i,j,t}$. It is reasonable to argue that climate anomalies will be reflected in coffee price fluctuations. If psychological price barriers are not present, then the estimated coefficients on $sst_{t-i}^{(+)}$ and $sst_{t-i}^{(-)}$ explaining the dummy dependent variable will be insignificant. In this stage of the analysis, we do not focus on specific regressors, or on the signs and magnitude of their estimated coefficients. Instead, we focus on the challenge of selecting the variables $sst_{t-i}^{(+)}$ and $sst_{t-i}^{(-)}$ that correlate well with the variable to be predicted, which can be viewed as a problem of multiple testing. We also include $d_{i,j,t-1}$ in the right-hand side of Eq. (4) to give some indication of inertia or persistence in the barrier. We employ the daily measure of weather anomalies described above, where we specifically set $n = 30$ in Eq. (4). This means that there is the challenge of variable selection in the presence of a large number of regressors. We approach this prediction problem using OCMT, a novel OLS regression-based variable selection method recently proposed by Chudik et al. (2018).[16]

OCMT tests the statistical significance of all covariates $d_{i,j,t-1}$, $sst_{t-i}^{(+)}$ and $sst_{t-i}^{(-)}$ one at a time, and selects those whose t-statistics are greater, in absolute terms, than a given critical value; see Appendix C for details on the application of OCMT in the context of Eq. (4). Looking first at the hundreds digits, model selection results for the proximity variable $d_{00,00,t}$, not reported here, indicate that only in `mex` coffee covariates are selected; more specifically, we find twenty-five (out of the thirty-one) covariates $sst_{t-i}^{(-)}$ correlating well with the variable to be predicted. However, when proximity to the 00 price is measured by the variables $d_{98,02,t}$, $d_{95,05,t}$, and $d_{90,10,t}$, an increasing number of covariates are selected, as illustrated in Table 7 for the widest case of $d_{90,10,t}$.

Table 7 reveals a varied pattern of correlation between proximity and (current and past) climate anomalies, in the sense that for some coffee varieties both positive and negative anomalies appear relevant (`col`, `gua`, `mex`, `idn`, and `uga`), whereas for others only positive (`vnm`) and only negative (`bra`) anomalies are important. The number of covariates that enters in each coffee variety model also varies noticeably. The barrier proximity and hump tests reported earlier for `bra`, `idn`, `uga` and `vnm` are suggestive of positive rather than negative clustering at the 00-centred barriers. The significant outcomes reported here are consistent with this. In addition, OCMT selects $d_{i,j,t-1}$ in all models; the average value of the estimated coefficients on this variable is 0.90 revealing a great degree of persistence in the barrier. As for tens digits, results not reported here indicate that OCMT does not pick up covariates for any of the coffee varieties. This is perhaps an expected result as we found little evidence in favour of psychological price barriers for these digits. In this case, the average value of the coefficients associated to $d_{i,j,t-1}$ is 0.38, suggesting that more than 60% of a shock disappears within a day.

Climate anomalies might be reflected in coffee price fluctuations. Here we have provided new insights with evidence that climate impacts significantly on the likelihood of coffee prices being in the proximity of a psychological 00 price. If we focus on the hundreds digits, then for most of our sample, both positive and negative climate anomalies are significant. Asymmetries are present in the cases of `bra` and `vnm` insofar as a significant anomaly effect depends on respective below- or above-normal SST values.

Finally, we can consider a possible implication of our findings. If there is indeed clustering at the 00-centred barriers, then one might expect that the actual (or untransformed) individual coffee prices are less responsive to SST anomalies than the price indices derived from these prices, where the price rigidities around the 00-centred barriers are averaged across varieties. So one might ask if the actual prices are less responsive to SST deviations than what has been presented using the dummy time-series variables? To address this question, we can estimate an autoregressive distributed lag (ARDL) model for each coffee price as a function of past values of itself and current and past values of SST anomalies. We can then generate a "price index" as a simple average across the seven coffee varieties available and estimate the corresponding ARDL model to the resulting price aggregate. Results not reported here indicate that there are some negative short-run SST effects in the cases of `bra`, `gua`, and `mex`. Thus, on that basis, it would appear that the individual untransformed price series are generally less responsive to SST deviations. We view that these initial findings justify a formal and rigorous re-examination of the potential linkages between SST anomalies and coffee prices, which is a task that constitutes a research topic for another paper.

5. Concluding remarks

We employ a novel database of daily prices for seven coffee varieties over a twenty-year study period to provide new insights into the dynamics of coffee prices in the short run. Focusing on the presence and impact of psychological price barriers, we conclude

[14] It is worth reiterating that $d_{i,j,t}$ is a time-series variable, while $d_{i,j}$ in Section 3.2 is a cross-section variable.

[15] We obtain qualitatively similar findings if instead of using positive and negative SS deviations, we use positive and negative deviations with respect to the mean of actual temperature.

[16] The results were obtained using the user-written command `ocmt` developed for the Stata environment by Núñez and Otero (2021).

Table 7
Weather conditions and proximity of hundreds digits to 00.

i	bra		col		gtm		mex		idn		uga		vnm	
	sst^{+}_{t-i}	sst^{-}_{t-i}	sst^{+}_{t-i}	sst^{-}_{t-i}	sst^{+}_{t-i}	sst^{-}_{t-i}	sst^{+}_{t-i}	sst^{-}_{t-i}	sst^{+}_{t-i}	sst^{-}_{t-i}	sst^{+}_{t-i}	sst^{-}_{t-i}	sst^{+}_{t-i}	sst^{-}_{t-i}
0		✓		✓	✓		✓	✓	✓	✓	✓	✓		
1		✓		✓	✓		✓	✓	✓	✓	✓	✓		
2		✓		✓	✓		✓	✓	✓	✓	✓	✓		
3		✓	✓	✓	✓		✓	✓	✓	✓	✓	✓		
4		✓	✓	✓	✓		✓	✓	✓	✓	✓	✓		
5		✓	✓	✓	✓		✓	✓	✓	✓	✓	✓		
6		✓	✓	✓	✓		✓	✓	✓	✓	✓	✓		
7		✓	✓	✓	✓		✓	✓	✓	✓	✓	✓		
8		✓	✓	✓	✓		✓	✓	✓	✓	✓	✓		
9		✓	✓	✓	✓		✓	✓	✓	✓	✓	✓		
10		✓	✓	✓	✓		✓	✓	✓	✓	✓	✓		
11		✓	✓	✓	✓		✓	✓	✓	✓	✓	✓		
12		✓	✓	✓	✓		✓	✓	✓	✓	✓	✓		
13		✓	✓	✓	✓		✓	✓	✓	✓	✓	✓		
14		✓	✓	✓	✓		✓	✓	✓	✓	✓	✓		
15		✓	✓	✓	✓		✓	✓	✓	✓	✓	✓		
16		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		
17		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		
18		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		
19		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		
20		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		
21		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		
22		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
23		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
24		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
25		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
26		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
27		✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	
28		✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	
29		✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	
30		✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	

Note: The dependent variable is a dummy variable $d_{i,j,t}$, which measures the length of the price barrier in the range from i to j in the neighbourhood around $M = 00$ at time t, with $\{i, j\}$ defined over the interval $\{90, \ldots, 00, \ldots, 10\}$; see equation (4). The symbol ✓indicates the variables selected by OCMT, based on $\delta = 1$, $\delta^{\star} = 2$, and significance level $\mathrm{p} = 0.01$. In all models OCMT selects $d_{i,j,t-1}$.

that there are prices to which market participants attach more importance than others. More specifically, by examining the hundreds digits, we confirm negative clustering at psychological 00 price barriers for the more expensive, higher-quality arabica coffees. We also uncover psychological barriers between arabica and robusta price differentials, suggesting that for the less expensive robusta coffees, the impact of psychological price barriers is perhaps indirect, applying only to price differentials. Additionally, we find evidence of changing dynamics in coffee price returns in the days before and after breaching these barriers, as well as further support for psychological barriers through the significant effects of El Niño and La Niña on coffee pricing in proximity to such obstacles.

Coffee farmers are interested in understanding the nature of coffee price fluctuations. Indeed, the stability of coffee prices has been an important issue in the minds of national governments, producers, and consumers alike. We contribute to the existing literature by unearthing evidence of a type of rigidity or impediment to the movement of coffee prices that is not explained by economic fundamentals but instead takes the form of psychological barriers, whereby market participants assign particular importance to specific price levels. Based on several econometrically significant results, we find that more substantial barriers exist for high-quality arabica coffees rather than robusta coffees. Despite the raw data evidence indicating slightly higher price variability for arabica coffees compared to robusta, our findings suggest that arabica coffee prices are occasionally more stable near 00-centred price barriers. This potential can assist policymaking related to understanding price behaviour and the income variability of coffee farmers. Improved knowledge of coffee price dynamics provides a better understanding of factors impacting the future well-being and livelihoods of farmers who supply arabica varieties.

From here, there are several potential avenues for future research. Our results suggest that there may be other profound and highly influential behavioural factors in coffee pricing that future research should investigate. If psychological barriers are having an impact, it is pertinent to ask what other factors, not rooted in economic fundamentals, might also affect and further shape policy design. Other avenues of research might include pursuing a deeper understanding of the links between quality variation across a range of commodities and the positioning of price barriers that may not necessarily involve a 00 price. This could lead to potential common and commodity-specific policy prescriptions shaped by an improved understanding of commodity price stickiness or rigidity. Finally, another avenue could focus on coffee and consider the role of psychological price barriers in assessing efficiency in the futures market and the ability to reduce uncertainty over future spot prices.

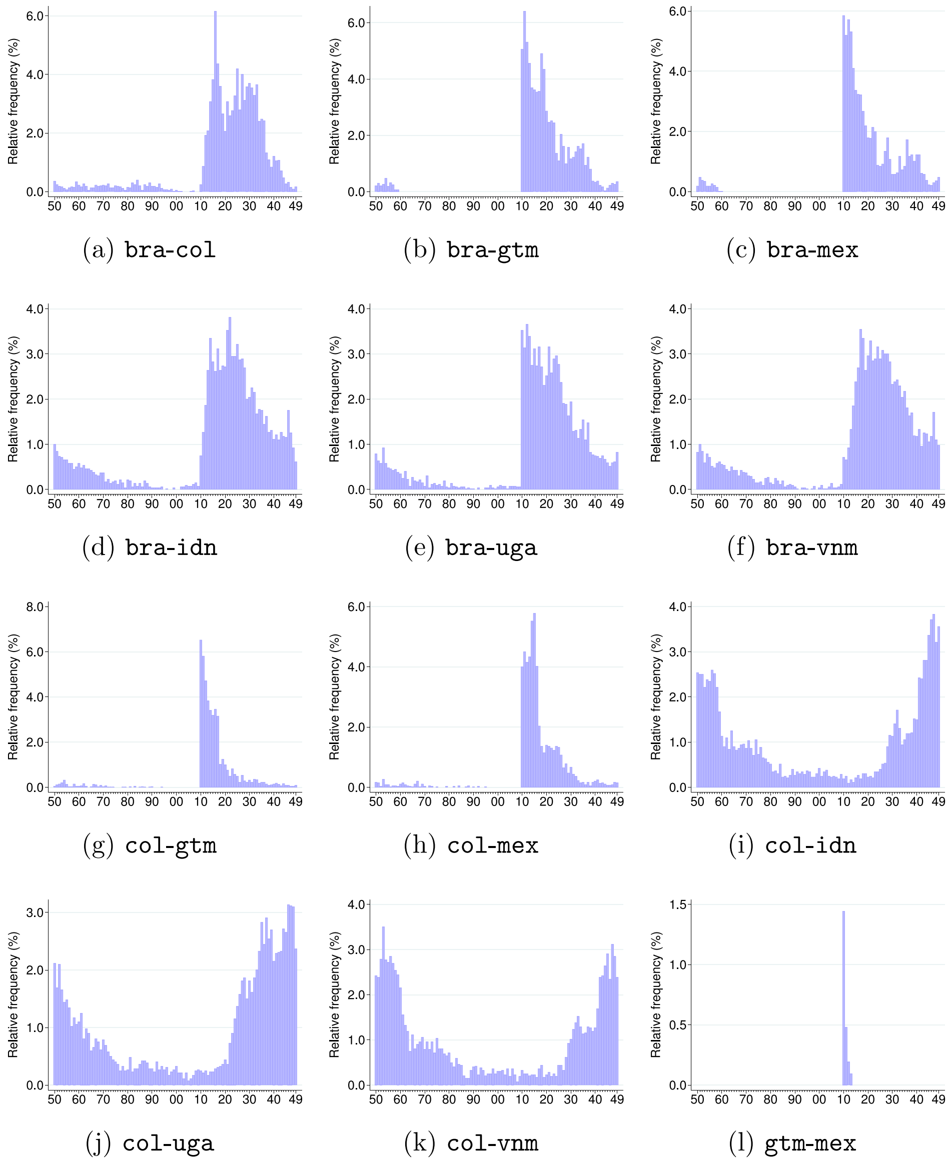

Fig. A.1. Absolute coffee price differentials.

CRediT authorship contribution statement

Mark J. Holmes: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing – review & editing, Writing – original draft. **Jesús Otero:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Visualization,Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

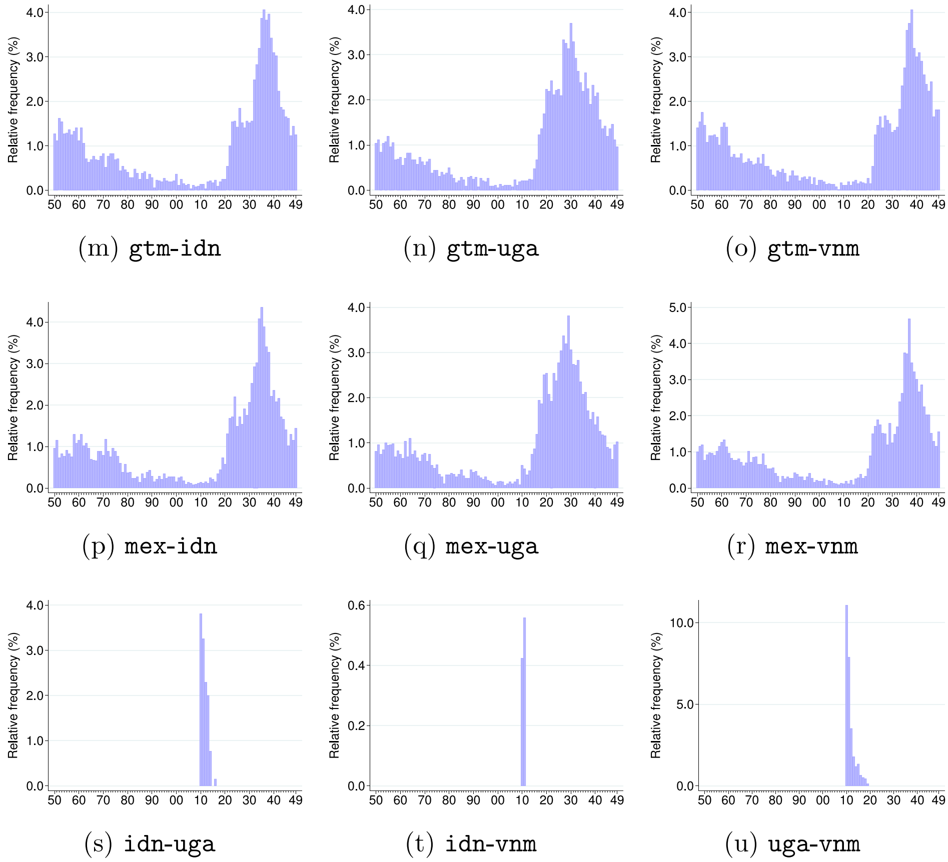

Fig. A.1. (*continued*).

Appendix A. Relative frequency of hundreds of US cents around 00 price digits

See Fig. A.1.

Appendix B. Relative frequency of tens of US cents around 00 price digits

See Fig. B.1.

Appendix C. Variable selection using OCMT

This Appendix offers an overview to variable selection in high-dimensional linear regression models using a one covariate at a time, multiple testing (OCMT) algorithm.

Drawing on Chudik et al. (2018), and applied to the context of variable selection in Eq. (4), OCMT tests the statistical significance of all covariates $d_{i,j,t-1}$, $sst^{(+)}_{t-i}$, and $sst^{(-)}_{t-i}$ one at a time, and selects those whose t-statistics are greater, in absolute terms, than a given critical value. The critical value is computed using the critical value function $c_p(N,\delta) = \Phi^{-1}\left(1 - \frac{\mathrm{p}}{2f(N,\delta)}\right)$, where $\Phi^{-1}(\cdot)$ is the inverse of the standard normal distribution function, $f(N,\delta) = cN^{\delta}$ for some positive constants $c = 1$ and δ, where the latter parameter is the so-called critical value exponent, $0 < \mathrm{p} < 1$ is the nominal size of the individual tests statistics, and N is the number of covariates in Eq. (4). All the covariates that satisfy the condition already stated are selected jointly to form an initial model specification. In a second stage, OCMT uses this initial model specification, and once again tests the statistical significance of the covariates which were not selected before one at a time. The procedure continues until there are no more statistically significant covariates. Chudik et al. (2018) point out that OCMT is fast because the number of stages needed for convergence is bounded by the number of covariates. To account for the multiple testing nature of the problem, the critical value function in the second and

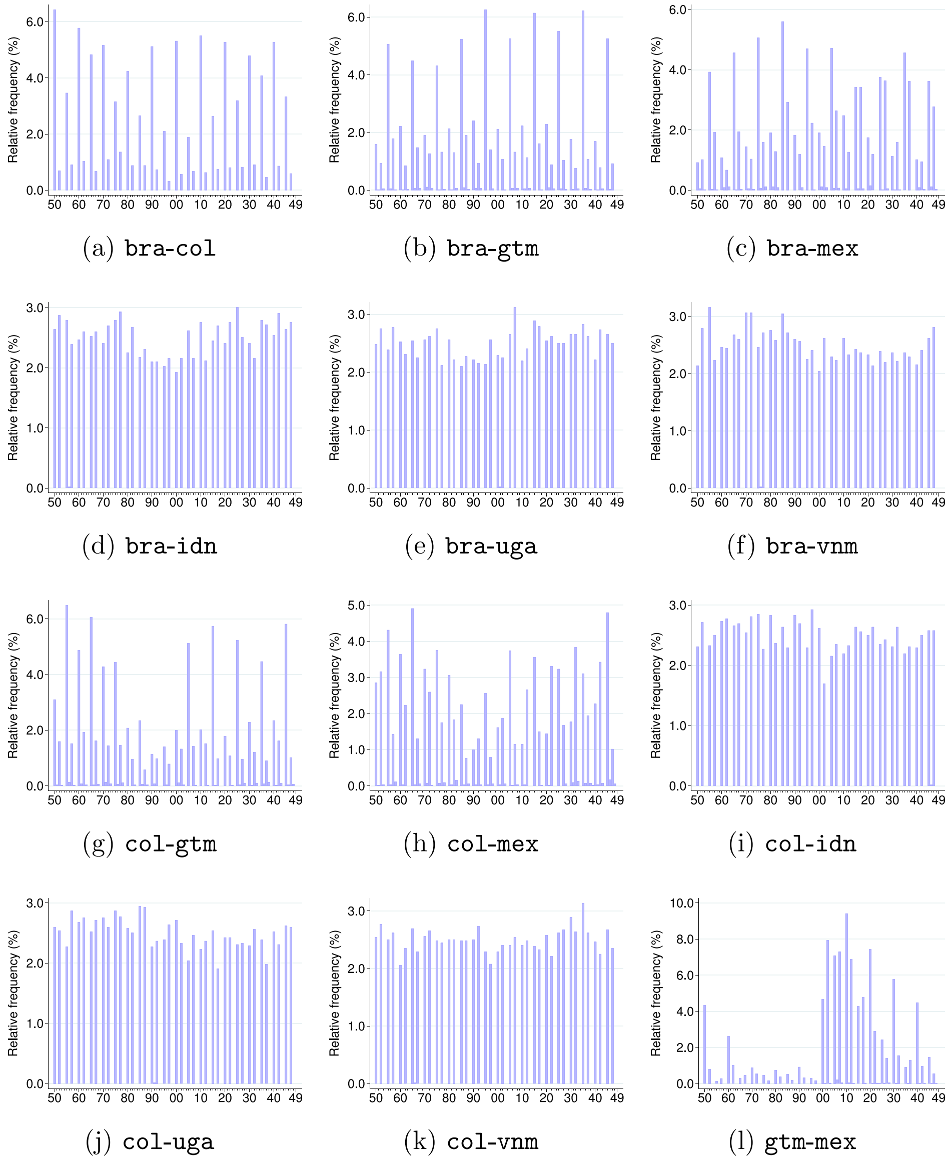

Fig. B.1. Absolute coffee price differentials.

subsequent stages of OCMT is given by $c_p(N,\delta^\star) = \Phi^{-1}\left(1 - \frac{\mathrm{p}}{2f(N,\delta^\star)}\right)$, where it is required that $\delta^\star > \delta$. Compared to other machine learning methods such as stepwise regression, OCMT offers the advantage of accounting for the multiple testing nature of the variable selection problem, as the critical value function in the second and subsequent stages is different from that used in the first stage.

In their Monte Carlo simulations and empirical illustration, CKP set the value of $\delta = 1$ which is equivalent to applying the well-known Bonferroni correction to the critical value from the standard normal distribution, for a given significance level p. As for the value of $\delta^\star$, we follow CKP and set it equal to 2. It proves useful to think of the positive constants δ and $\delta^\star$ as fine-tuning parameters that play the role of adjusting the critical values used for inference. For our purposes, we implement OCMT using $n = 30$ lags of each covariate $sst^{(+)}_{t-i}$ and $sst^{(-)}_{t-i}$, and setting $\delta = 1$ and $\delta^\star = 2$, with a significance level $\mathrm{p} = 0.01$. It is worthy of mention that to assess the robustness of our findings, we also varied n between 10 and 50, and set $\delta^\star = 1.5$. These additional parameter specifications yielded qualitatively similar results.

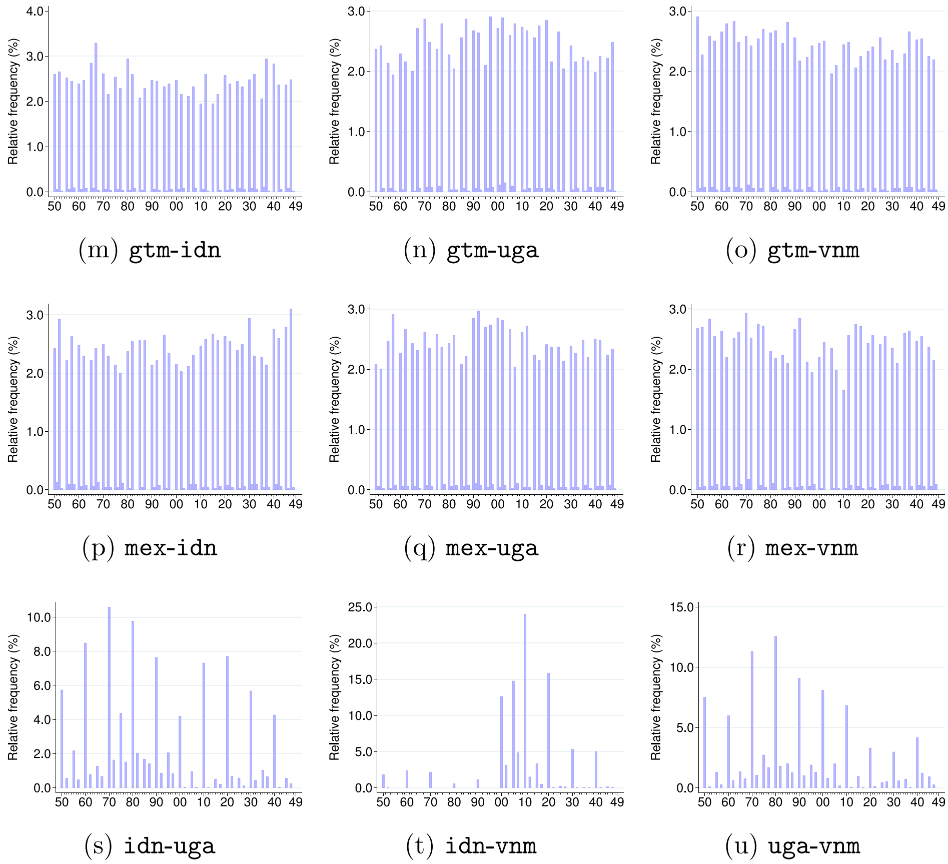

Fig. B.1. (*continued*).

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