1   **Pupil responses to pitch deviants reflect predictability of melodic sequences**

2   Roberta Bianco [a] *, Lena Esther Ptasczynski [b], Diana Omigie [b]

3   [a] Ear Institute, University College London, 332 Grays Inn Road, WC1X 8EE London, United Kingdom

4   [b] Department of Psychology, Goldsmiths, University of London, 8 Lewisham Way, SE14 6NW London,
5   United Kingdom

6   ***Correspondence:**
7   Roberta Bianco
8   r.bianco@ucl.ac.uk
9

10

12   **ABSTRACT**

13   Humans automatically detect events that, in deviating from their expectations, may signal prediction
14   failure and a need to reorient behaviour. The pupil dilation response (PDR) to violations has been
15   associated with sub- cortical signals of arousal and prediction resetting. However, it is unclear how the
16   context in which a deviant occurs affects the size of the PDR. Using ecological musical stimuli that we
17   characterised using a computational model, we showed that the PDR to pitch deviants is sensitive to
18   contextual uncertainty (quantified as entropy), whereby the PDR was greater in low than high entropy
19   contexts. The PDR was also positively correlated with the unexpectedness of notes. No effects of music
20   expertise were found, suggesting a ceiling e effect due to enculturation. These results show that the
21   same sudden environmental change can lead to differing arousal levels depending on contextual
22   factors, providing evidence for a sensitivity of the PDR to long-term context.

23   **Introduction**

24   The experience of surprise is very common in the sensory realm and often triggers automatic changes
25   in arousal and attentional states that are fundamental to adaptive behaviours. Music is a ubiquitous
26   and ecological example of a situation where changes in listeners' arousal and attention are
27   intentionally manipulated. Composers may, for example, modulate the predictability of musical
28   passages in order to achieve differing levels of tension in a listener. A great deal of empirical work has
29   shown that surprising sounds are recognised by listeners in an effortless and automatic fashion
30   (Pearce, 2018). This process is thought to be supported by a mismatch between the current
31   unexpected input and the implicit expectations made possible by schematic and dynamic knowledge
32   of stimulus structure (Huron, 2006; Krumhansl, 2015; Tillmann, Bharucha, & Bigand, 2000; Vuust &
33   Witek, 2014). However, there is still rather little research examining mismatch responses under
34   different degrees of uncertainty during passive listening.

35   Evidence of listeners experiencing events in music as unexpected comes from studies investigating
36   behavioural (Marmel, Tillmann, & Delbé, 2010; Omigie, Pearce, & Stewart, 2012; Tillmann & Lebrun-
37   Guillaud, 2006) and brain responses to less regular musical events (Bianco, Novembre, Keller, Kim, et
38   al., 2016; Carrus, Pearce, & Bhattacharya, 2013; Koelsch, 2016; Koelsch, Gunter, et al., 2002; Maess,
39   Koelsch, Gunter, & Friederici, 2001; Miranda & Ullman, 2007; Omigie, Pearce, Williamson, & Stewart,

40 2013; Pearce, Ruiz, Kapasi, Wiggins, & Bhattacharya, 2010). With regard to the former, priming
41 paradigms have shown that a context allows perceivers to generate implicit expectations for future
42 events, leading to facilitated processing (i.e., priming) of expected events. With regard to the latter,
43 violation paradigms have shown increased brain responses to deviant events (out of key notes, or
44 harmonically incongruent chords) within structured contexts as well as events which are musically
45 plausible but more improbable in the given context. For example, Omigie et al. (2013) tested brain
46 responses to melodies whose notes were characterised in terms of their predictability by a model of
47 auditory expectations (Pearce, 2005). They showed that surprising events (more improbable notes)
48 within melodies elicited a mismatch response – often termed the mismatch negativity, MMN (Garrido,
49 Kilner, Stephan, & Friston, 2009; Näätänen, Paavilainen, Rinne, & Alho, 2007). This response decreased
50 in amplitude for progressively more predictable events, as estimated by a computational model of
51 melodic expectation. A similar parametric sensitivity to note unexpectedness has since also been
52 observed in subcortical regions like the anterior cingulate and insula (Omigie et al., 2019). Moreover,
53 sensitivity to music structure violation seems to emerge in all members of the general population that
54 have had sufficient exposure to a given musical system (Bigand & Poulin-Charronnat, 2006; Pearce,
55 2018; Rohrmeier, Rebuschat, & Cross, 2011), and this sensitivity is modulated by pre-existing
56 schematic knowledge of music, as reflected in acquired levels of musical expertise (Fujioka, Trainor,
57 Ross, Kakigi, & Pantev, 2004; Koelsch, Schmidt, & Kansok, 2002a; Tervaniemi, 2009; Vuust, Brattico,
58 Seppänen, Näätänen, & Tervaniemi, 2012).

59 According to theoretical and empirical work framing perception in the context of predictive processing,
60 the experience of surprise may be modulated by the predictability of a stimulus structure as it unfolds
61 (Clark, 2013; Dean & Pearce, 2016; Friston, 2005; Ross & Hansen, 2016). Random or high entropic
62 stimuli hinder the possibility of making accurate predictions about possible upcoming events, whilst
63 stimuli characterized by familiarity or regular statistics will enable relatively precise predictions by
64 permitting the assignment of high probability to a few possible continuations. Perceptually, it has been
65 shown that listeners indeed experience high-entropic musical contexts with greater uncertainty
66 compared to low entropy ones (Hansen & Pearce, 2014). Moreover, previous work has shown that
67 neurophysiological signatures associated with auditory surprise display larger responses to a given
68 deviant event when it is embedded in a low rather than high entropic context (Dean & Pearce, 2016;
69 Garrido, Sahani, & Dolan, 2013; Hsu, Le Bars, Hamalainen, & Waszak, 2015; Ricardo Quiroga-Martinez,
70 2018; Rubin, Ulanovsky, Nelken, & Tishby, 2016; Southwell & Chait, 2018). Therefore, research
71 suggests that to understand whether and how surprising events modulate arousal and re-orient
72 behaviours, the statistics of the proximal context must be considered.

73 A vast literature has used pupil dilation response (PDR) as a general marker of arousal, selective
74 attention, and surprise (Aston-Jones & Cohen, 2005; Sara, 2009). Pupil dilation is associated with the
75 locus coeruleus-norepinephrine (LCN) system (Laeng, Sirois, & Gredeback, 2012; Widmann, Schröger,
76 & Wetzel, 2018), the activation of which results in wide spread norepinephrine release in the brain.
77 Increase of the PDR has been extensively reported in response to violation of expectations or
78 surprising/salient events in distracted listeners (Damsma & van Rijn, 2017; Liao, Yoneya, Kidani,
79 Kashino, & Furukawa, 2016; Wetzel, Buttelmann, Schieler, & Widmann, 2016; Zhao et al., 2019), and
80 when deviants are presented below participants' perceptual threshold (Fink, Hurley, Geng, & Janata,
81 2018). Furthermore, a relationship between PDR and continuous ratings of surprisal in music
82 (measured via a continuous slider) has been reported during passive listening (Liao, Yoneya, Kashino,
83 & Furukawa, 2018). Other work has specifically associated the PDR to violations of statistical
84 regularities in the sensory input even when these violations are behaviourally irrelevant (Alamia,

85   VanRullen, Pasqualotto, Mouraux, & Zenon, 2019; Zhao et al., 2019). These results provide supporting
86   evidence for a role of norepinephrine in the tracking of abrupt deviations from the current predictive
87   model of the world, and as a signal of prediction resetting that enables the discovery of new
88   information (Dayan & Yu, 2006).

89   Music has the ability to play with our expectations, hence manipulating our arousal and emotions in
90   an automatic fashion (Laeng, Eidet, Sulutvedt, & Panksepp, 2016; Meyer, 2001; Zatorre & Salimpoor,
91   2013). Abrupt changes in register, texture and tonality are all examples of instances where the listener
92   may have to reset or potentially abandon current models about the unfolding music. Such changes
93   may however appear less surprising if embedded in high entropy contexts. Here, we use music as an
94   ecological setting with which to study how the PDR to deviant musical events is modulated by structure
95   of the stimulus context, specifically by its entropy. The growing field of computational musicology
96   means that information in melodies can be statistically estimated. One particular model of auditory
97   expectations – the Information Dynamics of Music, IDyOM (Pearce, 2005) – has been shown to model
98   listeners' experience of surprise and uncertainty. This unsupervised Markov model learns and
99   estimates the conditional probability of each subsequent note in a melody based on a corpus on which
100   it has been trained (long-term sub-model; extra-opus-learning) and the given melody as it unfolds
101   (short-term sub-model; intra-opus learning). The model outputs information content and entropy
102   values, which, respectively, reflect the experienced unexpectedness of a certain note after its onset
103   and the experienced uncertainty in precisely predicting a subsequent note based on the preceding
104   pitch probabilities.

105   We created novel melodies (Figure 1) that adhered to the principles guiding Western tonal melodic
106   structure. We then created shuffled versions of these melodies to create stimuli that were higher in
107   entropy albeit matched for pitch range, content and tonal space. The information theoretic properties
108   of all stimuli were estimated using IDyOM (Pearce, 2005). Listeners were presented with these
109   melodies either in their standard form or with a pitch deviant whilst PDR was measured. Participants
110   were not informed about the presence of the pitch deviants, but asked to rate the unexpectedness of
111   last note of each melody. We expected a larger PDR to deviant notes that are embedded in low rather
112   than high entropy contexts, and that are higher in their unexpectedness – information content value
113   – as estimated by the computational model. Also, we expected entropy of the melodies to predict
114   subjective ratings of stimulus unexpectedness (Hansen & Pearce, 2014). Finally, based on evidence of
115   greater brain response to musical violations in musicians than non-musicians (Vuust, Brattico,
116   Seppänen, Näätänen, & Tervaniemi, 2012b), presumably reflecting expertise-related enhancement in
117   the accuracy of predictive models, differences due to musical expertise (Müllensiefen et al., 2014) were
118   also investigated.

119   **Methods**

120   *Participants*

121   Forty-seven participants (age: *M*=26.19, *SD*=6.24, min.=20, max.=52, 68% female, representing 15
122   nationalities) took part in the study. The sample scored relatively high on the general musical
123   sophistication index, GoldMSI (Müllensiefen et al., 2014), with *M*=87.40, *SD*=25.24, min.=32,
124   max.=120. A big sample size was chosen based on a previous experiment using musical stimuli (Laeng
125   et al., 2016) and to ensure statistical power. As a post-hoc confirmation of the adequacy of our sample-
126   size, we quantified effect sizes of the difference between PDR to deviants in high vs. low entropy
127   contexts. The power analysis was conducted in the G*Power software package (version 3.1.9.2) with

128 the setting p = .05 and N = 42 and confirmed that our sample size was adequate (1 − β > .9). Two
129 participants reported ophthalmologic concerns or surgery prior to the experiment but were not
130 excluded from participation as the pupil dilates even in blindsight participants (Weiskrantz, Cowey, &
131 Barbur, 1999). Technical problems occurred during the recording of four participants, who were
132 therefore excluded from the analysis. One subject was further excluded as blink gaps were too large
133 to be interpolated. In sum, forty-two participants' data were analysed.

134 Ethical approval for this study was granted by the Research Ethics Committee of Goldsmiths, University
135 of London. Participants were instructed as to the purpose of the study, and consented to participate
136 (written informed consent). Participation was remunerated with 5 pounds.

137 *Stimuli*

138 One-hundred-twenty melodies were used in this study (thirty originally composed, thirty matched
139 'shuffled' versions, and sixty corresponding versions with a deviant tone always as the 13th note). The
140 melodic sequences comprised 20 tones, were 5 seconds long, isochronous (with an inter-onset-interval
141 of 250 ms, 20/4 bar with 240 bpm), and had constant intensity and timbre (MIDI generated piano
142 timbre).

143 The corpus of melodies was composed according to the principles of Western-tonal music and using
144 all tones of the chromatic scale. Ambitus and tonal space varied across melodies. Interval size did not
145 exceed a perfect fifth (Narmour, 2015) between adjacent notes. Thus, the original melodies were
146 characterized by a smooth contour. To generate matched melodies that controlled for potential biases
147 such as tonal space, pitch class, frequency range or ambitus, high entropy melodies were created from
148 the original melodies by randomizing the order of constituent notes using MIDI processing tools (Eerola
149 & Toiviainen, 2004). Our manipulation of entropy, whereby notes in original melodies were randomly
150 shuffled without constraint, necessarily resulted in the mean absolute interval size being greater in
151 high entropy than in low entropy melodies [L vs. H: t(58) = -2.644, p-value = .01]. Corpus studies of
152 western tonal music show that large interval sizes are much less common than small ones (Huron,
153 2001). Thus, we anticipated that the presence of such large intervals would lead to the higher entropy
154 levels desired for the high entropy condition.

155 Deviant notes were inserted in all 60 melodies (original and shuffled version) at the onset of the 13th
156 note (3000ms on the salient onbeat) in order to create the corresponding set of *deviant melodies* (Fig.
157 1). The deviant note was integrated into the second half of the melody in order to allow the
158 establishment of an expectation-forming context before its occurrence. To ensure that differences in
159 the PDR to the deviant notes between low and high entropy condition were not attributable to
160 difference in the just preceding event, but to the context, the interval size between the deviant and
161 the preceding 12th note was the same in matched pairs of high and low entropy melodies (see Fig. 1).
162 However, interval size of the deviant varied between maj7 up/down, min9 up/down and aug11
163 up/down as those intervals sound particularly unusual within a melodic progression. Larger interval
164 size of the deviant was assigned to matched pairs with lower entropy differences. This allowed for a
165 variety of deviant interval sizes (a range of unexpectedness) while ensuring salience of deviants even
166 in melodies showing relatively smaller entropy differences.

167 Entropy values were assigned by the IDyOM model to each note of the melodies. The IDyOM model
168 considered one pitch viewpoint, namely 'cpitch', whereby chromatic notes count up and down from
169 the middle pitch number (C=60) (Pearce, 2005). Through a process of unsupervised learning, the model
170 was trained on a corpus (903 Western tonal melodies) comprising songs and ballads from Nova Scotia

in Canada, German folk songs from the Essen Folk Song Collection and chorale melodies harmonised by J.S. Bach. The probability of each note of the stimulus used here were then estimated based on a combination of the training set's statistics and those of the given melody at hand. The model outputs information content and entropy values. In mathematical terms, information content is inversely proportional to the probability of an event x_i, with $IC(x_i) = -\log_2 p(x_i)$ (MacKay, 2003), while the maximum entropy is reached when all potential events x_i are equally probable, with $p(x_i) = 1/n$, where n equals the number of stimuli. In psychological terms, information content represents how surprising each subsequent note is based on its fit to the prior context (Pearce & Wiggins, 2006). In contrast, entropy refers to the anticipatory difficulty in precisely predicting a subsequent note. Mean entropy values, obtained by taking the mean entropy of all notes, were used to characterise the predictability of each melody. Given our manipulation, mean entropy was largely, but not entirely, explained by the mean interval size of melodies (rho = .474, p < .001). These values were then used to predict subjective inferred uncertainty (measured as unexpectedness of last note) about each melody, and to categorise melodies into low and high entropy groups. By controlling that the interval preceding the deviant note was identical across high and low entropy condition, we predicted that a greater PDR to deviant notes in low than high entropy melodies should be attributable to the difference in the context.

Procedure

The experiment was presented using the Experiment Builder Software and pupil diameter was recorded using EyeLink 1000 eye-tracker at a 250Hz sampling rate (SR Research, www.sr-research.com/experiment-builder). Prior to the data acquisition, a three-dot calibration was conducted to ensure adequate gaze measurements. Participants were further allowed to adjust the sound volume to a comfortable level and were asked to reduce head movements to a minimum throughout the recording session. As no differences were anticipated between the left and right pupil, the left pupil was recorded in ten and the right pupil in 32 participants depending on the participants' dominant eye. To reduce motion artefacts, the head was stabilized using the SR Research Head Support chinrest placed 50 cm from the presentation screen.

During the experiment, the 120 melodies were presented binaurally through headphones in a randomized order. Each trial was triggered by the experimenter on the control computer when the fixation was stable at less than two arbitrary gaze units away from the fixation point. When recording was enabled, a white fixation dot on the grey screen turned black to prepare participants for the onset of the melody. The fixation cross was displayed for 7 seconds after stimulus onset. Each trial was preceded by a 400 ms baseline period and followed by a 2000 ms post stimulus offset. The melody was 5000 ms long and participants were instructed not to blink or move but to fixate during that whole period. Participants were allowed to take breaks to avoid fatigue effects at their convenience. A re-calibration procedure using the 3-dot-calibration was applied after each break.

Participants were instructed to carefully listen to the melody while fixating on the fixation point in the centre of the screen throughout the recording period. They were not informed about the deviant manipulation. After each trial, participants rated the final note on a Likert-scale ranging from 1 (not at all unpredictable) to 7 (extremely unpredictable) in a forced-choice task on the presentation screen. Data on the subjects' musical expertise and sociodemographic background was collected at the end of each experiment using the GoldMSI (Müllensiefen et al., 2014). The whole study lasted approximately one hour.

Data pre-processing

214   Blinks were identified and removed from the signal using MATLAB R2017b. These were characterized
215   by a rapid decline towards zero from blink onset, and a rapid rise back to the regular value at blink
216   offset. 100ms of the signal was removed before and after the missing data points (Troncoso, Macknik,
217   & Martinez-Conde, 2008) and missing data were interpolated: four equally spaced time points were
218   used to generate a cubic spline fit to the missing time points between blink onset (t2) and blink offset
219   (t3) of the unsmoothed signal, with t1= t2-t3+t2 and t4= t3-t2+t3 (Mathôt, Fabius, Van Heusden, & Van
220   der Stigchel, 2018). Trials containing more than 15% missing data were excluded from the analysis (*M*=
221   .3, *SD* = .9 trials across subjects). Data were cleaned of artefacts using Hampel filtering (median filtered
222   data; Pearson, Neuvo, Astola, & Gabbouj, 2016), and smoothened using a Savitzky-Golay filter of
223   polynomial order 1 over the entire trial epoch. Finally, data were z-scored, and then baseline-corrected
224   by subtracting the median pupil size of 400 ms baseline before melody onset. To analyse the time-
225   window after deviant onset, data were baselined from 400 ms before deviant onset. The normalized
226   pupil diameter was time-domain-averaged across trials of each condition.

227   *Experimental design and statistical analysis*

228   We estimated a single time series for each sequence type: low or high entropy with either standard or
229   deviant note type (*S-Low/D-Low/S-High/D-high*) by averaging across trials and participants. Statistical
230   analysis was performed using Fieldtrip's cluster-based permutation test (Maris & Oostenveld, 2007),
231   with a significance threshold at 5% to control family-wise error-rate (FWER). This analysis revealed the
232   time windows showing significant difference between the compared time series.

233   We first compared responses to deviant notes in the low and high entropy contexts with the
234   corresponding standard notes using signals recorded across the entire melody duration (baselined 400
235   ms before melody onset). This ensured that differences between deviant and corresponding standards
236   were not due to differences in the immediately preceding note. Then, to determine how the deviant
237   PDR is affected by the entropy of the melodic context, we focussed on the time window from deviant
238   onset to the end of the melody (3000 to 5000 ms epochs). We thus baselined to 400 ms before deviant
239   onset, and we tested for an interaction of the deviant and context manipulation: (*D-Low – S-low*) vs.
240   (*D-High – S-High*). Further, we compared the responses to standard tones in the two contexts (*S-Low*
241   *– S-High*) to ensure that any differences were not driven simply by the standard notes (the control
242   conditions).

243   To assess a potential influence of expertise on the PDR to deviants (data between 3000 and 5000 ms
244   baselined to 400 ms before deviant onset), we computed the mean PDR to deviant trials as *D-Low – S-*
245   *Low* for deviants in low entropy context, and *D-High – S-High* for deviants in high entropy context.
246   Participants were split into two groups of musical experts and non-experts based on GoldMSI scores
247   (*Mdn*=96). An ANOVA with within-subject factor context (low/ high entropy) and expertise as between-
248   subject factor (expert/non-expert) was computed.

249   **Results**

250   *Stimuli characterization*. Analyses were carried out to clarify the nature of all differences in information
251   theoretic properties of the different stimuli. Figure 1B (left panel) shows the mean entropy values for
252   all conditions (*D-Low*: *M* = 2.96, *SD* = .18; *D-High*: *M* = 3.09, *SD* = .19; *S-Low*: *M* = 2.86, *SD* = .19; *S-High*:
253   *M* = 3.03, *SD* = .23). An ANOVA with context (low/ high entropy) and note type (deviant / standard) as
254   between-group factors yielded a main effect of context [$F(1,116) = 15.20$, $p < .001$, $np2 = .12$],
255   indicating higher entropy in *High* than *Low entropy* melodies [$t(58) = 2.85$, $p = .006$]. A significant main
256   effect of note type [$F(1,116) = 5$, $p = .027$, $np2 = .04$], was not supported by a further post hoc

comparison [t(58) = -1.641, p = .11]. No interaction was found between the two factors [F(1,116) = .25, p = .617, $np2$ < .01].

Figure 1B (right panel) shows that the unexpectedness of deviant notes, as reflected by information content values, was comparable between low and high entropy melodies. An ANOVA with between group factors context (low / high entropy) and note type (deviant / standard) yielded a main effect of note type [F(1,116) = 239.02, p < .001, $np2$ = .67], a non-significant main effect of context [F(1,116) = .42, p = .517, $np2$ = .01], and no interaction between the two factors [F(1,116) = .00, p = .714, $np2$ < .01] – thus indicating higher information content in deviant than standard notes regardless of the context in which they were embedded [t(58) = -12.321, p < .001]. The similar IC levels of deviant for the two entropy conditions may be due to fact that in both low and high entropy contexts, deviants were similar in being characterised by very large interval departures away from the melodic contour (as opposed to the relatively naturalistic events that occurred in real melodies (Dean & Pearce, 2016). Critically, that deviant IC levels are similar for the two entropy conditions, supports our suggestion that stimulus context (and not just the IC level an incoming event) has the ability to modulate the PDR.

IC was positively predicted by interval size between the 12th and 13th note (rho = .862, p < .001), in line with research showing that amongst multiple psychological representations of pitch (e.g., height, contour, etc.), interval exerts a major contribution to perception of surprise (Levitin & Tirovolas, 2009; Pearce, 2018; Quiroga-martinez et al., 2019).
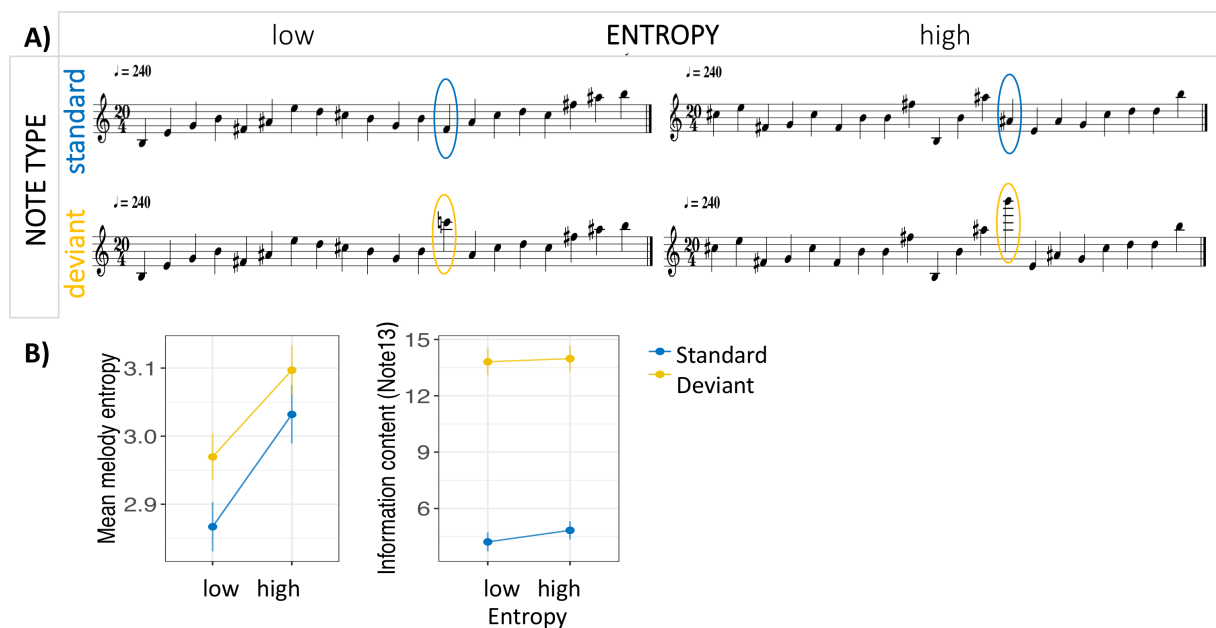
Fig. 1. Experimental design. Participants listened to the melodies of 20 notes and had to rate how unexpected they found the last note on a seven-step Likert scale (– 1 equal 'not at all unpredictable' and 7 'extremely unpredictable'). The design included two factors: Contextual entropy (low/high) and Note type (standard/deviant). Melodies containing deviant notes where 50% of the trials and the deviant notes occurred always at the 13th position. **B) Characterization of the stimuli.** A model of musical expectations was used to characterise the stimuli: Mean entropy was larger for high than low entropy melodies regardless of the presence of deviant (yellow) or standard (blue) tones. Mean information content of deviants (yellow) was larger than standard (blue) tones regardless of the entropy of the context.

PDR characterization. Figure 2A shows the time course of the PDR across conditions (*S-Low* = standard low entropy, *S-High* = standard high entropy, *D-Low* = deviant low entropy, *D-High* = deviant high entropy) baselined 400 ms before melody onset. A comparison between *S-Low* and *S-High* showed no difference in the PDR as a function of entropy levels of the melody, whilst the PDR to deviants (*D-Low* vs. *D-High*) was greater in predictable than unpredictable contexts (diverging at .56 s from deviant onset). The response to deviants in the predictable contexts was greater than the relative standard condition (*D-Low* vs. *S-Low*: p = .029), significantly diverging from *S-Low* between 3.57 and 5.64 s after melody onset. Conversely, the response to deviants in unpredictable contexts did not differ from the relative standard condition (*D-High* vs. *S-High),* despite their high information content (see Figure 1B, middle panel).

Figure 2B shows the PDR to deviants baselined 400 ms before deviant onset. We show the conditions *D-Low* and *D-High* following subtraction of the relative standard conditions. The comparison between the two time-courses confirmed that *D-Low* evoked a larger response than *D-High* starting at .59 s from deviant onset (p = .007) and ending at 1.5 s. Intrinsic noise in the baseline may explain the very early divergence between the curves, which however was not significant. Importantly, this pattern was observed in 67% of the participants (Figure 2C).

We run a post hoc analysis (Figure 3A) to investigate the relationship between the PDR related to the 13th note (including both standard and deviant notes) and associated information content for low and high entropy melodies. For each subject and for each melody, the average PDR to the 13th note was computed from the pre-deviant baseline (as in Figure 2B). A linear model with the factor context (Low /High) and information content as continuous variable was run to predict the PDR. This analysis yielded no main effect of context [$F(1,116)$ = .005, p = .941, *np2* < .001] and a main effect of information content [$F(1,116)$ = 4.911, p = .029, *np2* = .041] and a no significant interaction [$F(1,116)$ = 3.274, p = .073, *np2* = .027]. This suggests that the PDR is sensitive to a large range of unexpectedness levels.

We further investigated potential influences of expertise on the mean PDR to deviants (computed as *D-Low – S-Low* for deviants in low entropy contexts, and *D-High – S-High* for deviants in high entropy contexts on the data between 3000 and 5000 ms baselined to 400 ms before deviant onset as in Figure 2B). The ANOVA examining the effect of musical expertise on the mean PDR to deviants yielded a main effect of context [$F(1,40)$ = 5.09, p = .03, *np2* = .11]. The main effect of expertise was not significant [$F(1,40)$ = 3.72, p = .061, *np2* = .09], and no interaction between the two factors was seen [$F(1,40)$ = 2.18, p = .147, *np2* = .05]. This confirmed that the mean PDR to deviants was greater in low than high entropy contexts although no considerable difference between experts and non-experts was observed.

Finally, we showed that the model reliably predicted subjective uncertainty levels (inferred entropy) of the melody progressions (Hansen & Pearce, 2014) (Figure 3B). The measure of the unexpectedness of the last note was collected after participants listened to each melody. We found that the mean ratings for each melody strongly correlated with the information content of the last note of the melody (*rho* = .355, p < .001), and with the mean IDyOM entropy values for that melody (*rho* = .400, p < .001). This analysis validated our categorization of melodies based on the IDyOM output.

324
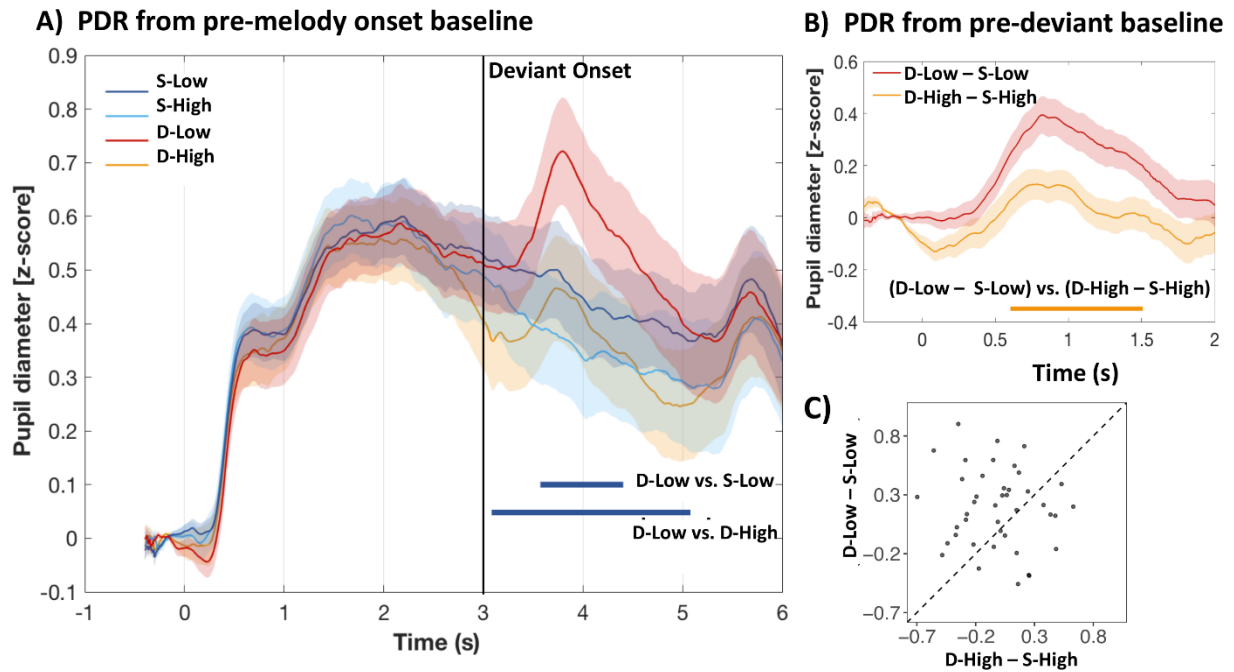
Fig. 2. A) The PDR for all conditions from melody onset (*S-Low* = standard low entropy, *S-High* = standard high entropy, *D-Low* = deviant low entropy, *D-High* = deviant high entropy). The PDR to deviants compared to standard tones (*D-Low* vs. *S-Low*) in low entropy contexts diverged between 3.57 and 5.64 s from melody onset (.57 s from deviant onset), but did not differ in high entropy contexts. Also, the PDR to deviants was greater in low than in high entropy contexts (*D-Low* vs. *D-High*) (diverging at 3.056 s from melody onset), but there was no significant context-dependent difference between the standard tones (*S-Low* and *S-High*). Shaded regions around the curves represent standard error in the mean estimated with bootstrap resampling (1000 iterations; with replacement). **B)** Interaction effect of deviant and context entropy on the PDR after deviant onset. The difference between the PDR to deviant and standard tones was greater in low than in high entropy contexts. This effect emerged .59 after deviant onset and ended at 1.5 s. **C)** The relationship between the PDR for *D-High – S-High* and *D-Low – S-Low* conditions. Each data point represents an individual participant. Dots above the diagonal reveal that 67% of participants showed a greater PDR to deviants in low compared with high entropy contexts.

339

340

341
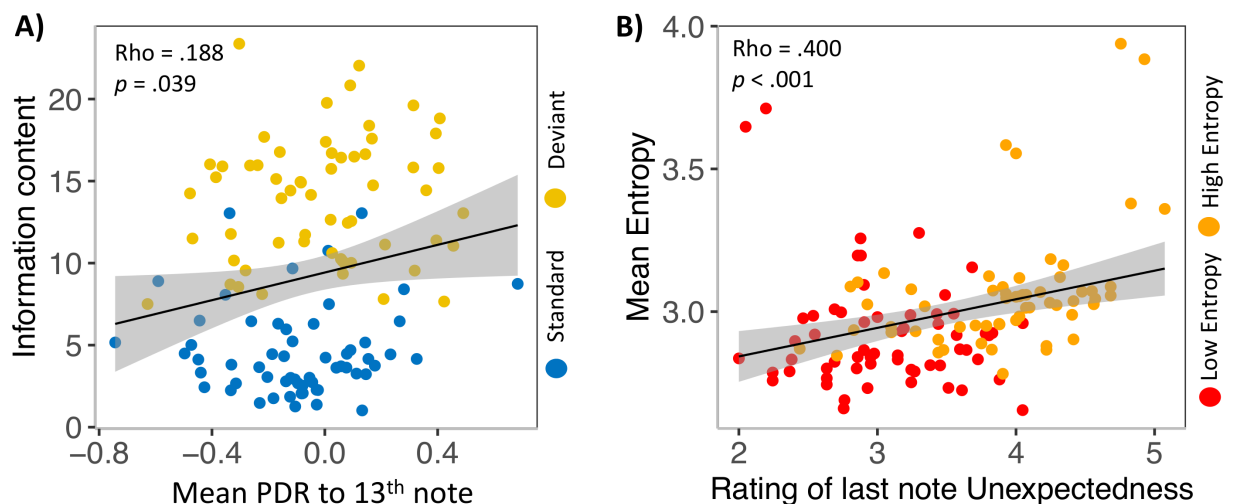
Fig. 3. A) The unexpectedness of the 13th notes (deviants and standards) was estimated by the IDyOM model and showed a positive correlation (Spearman) with the mean evoked PDR. Blue and yellow dots represent each of the standard and deviant notes. Shading represents s.e.m. **B)** The stimulus entropy was computed by the IDyOM model, and validated by participants' self-reports about the overall unexpectedness of each melody. Each dot represents one of the 120 melodies. Red and orange dots represent each of the low and high entropy melodies, respectively (N = 120). Shading represents s.e.m**.**

Discussion

We report that pupil dilation response (PDR) to behaviourally irrelevant deviants occurs when deviants are embedded in predictable rather than unpredictable melodies. We showed that the amplitude of the response is predicted by the information content (or unexpectedness) of the musical deviants. We also replicate the previous finding that listeners' experience of uncertainty is predicted by the entropy of the music (Hansen & Pearce, 2014). These results show that the same sudden environmental change leads to differing levels of arousal depending on whether it occurs in low or high states of uncertainty. Our results suggest that the more stable predictions formed in predictable rather than unpredictable contexts may be more abruptly violated by surprising events, possibly leading to greater changes in the listeners' arousal state.

The observed modulatory effect of context predictability on the PDR to deviants is consistent with a body of electrophysiological work showing context effects on mismatch like responses at the cortical level (Garrido et al., 2013; Quiroga-Martinez et al., 2019; Southwell & Chait, 2018). Here we show a similar pattern but in autonomic markers of arousal, as reflected by the PDR. Pupil response is thought to be driven by norepinephrine activity in the locus coeruleus (LC) (Joshi, Li, Kalwani, & Gold, 2016). This is a key subcortical nucleus which widely connects to the brain (Sara, 2009) to signal unexpected and abrupt contextual changes (Alamia et al., 2019; Damsma & van Rijn, 2017; Zhao et al., 2019). It has been hypothesised (Zhao et al., 2019) that MMN-related brain systems (Garrido et al., 2009; Hsu et al., 2015; Southwell & Chait, 2018) may trigger norepinephrine-mediated updating or interruption of ongoing top-down expectations. In line with this hypothesis, Alamia et al. (2019) have shown a correlation between pupillary response and MMN-like response evoked by violations of expectations, providing evidence of a link between the sources of these two responses. Top-down expectations about unfolding sensory signals have been associated with the temporo-frontal network in music-violation paradigms, which is thought to link present and past information to generate predictions about forthcoming events (Bianco, Novembre, Keller, Seung-Goo, et al., 2016; Koelsch, Gunter, et al., 2002; Tillmann, Janata, & Bharucha, 2003). Based on this existing evidence and in line with a model resetting hypothesis, our results suggest that listeners generate stronger predictive models (in the predictable melodies). These may be supported by temporo-frontal cortical regions, and require a greater signal (greater PDR) to be interrupted.

Albeit indirectly, our results also establish a link between subcortical and cortical activity in response to unexpected events under different states of uncertainty. Increased MMN response under low states of uncertainty (Quiroga-Martinez et al., 2019; Southwell & Chait, 2018) are replicated in the pupil response, reflecting a general increase in arousal. A possible interpretation, in line with the predictive coding theory (Friston, 2005), is that more stable expectations, representative of a strong predictive model, are reflected in precision-weighing of the prediction error, and hence a stronger response when the input mismatches the current predictions. Conversely, in high entropic contexts predictive models are weak, and the prediction error attenuated. This mirroring pattern between cortical (MMN) and subcortical (as reflected by the PDR) responses may have important behavioural advantages.

Specifically, strong predictive models can suddenly be abandoned when they are revealed to be erroneous, thus allowing speedy reorienting behaviours and quicker engagement with new potentially relevant stimuli. One limitation with regard to this possible interpretation is the nature of the deviant events used here, whereby the deviating event was a single note that did not lead to any long-lasting changes in the statistics of the unfolding sequence. Further studies combining cortical and pupil response measurements in continuously changing stimuli are necessary to corroborate our working hypothesis.

The absence of difference between high and low entropic contexts in the sustained pupil response (in the first half of the melodies) suggests that the pupil is relatively unresponsive to slowly unfolding stimulus structures, at least when listeners are not required to actively track them (Alamia et al., 2019; Zhao et al., 2019). Whilst cortical responses have been shown to be sensitive to the statistics of the unfolding stimulus structure (Barascud, Pearce, Griffiths, Friston, & Chait, 2016; Sohoglu & Chait, 2016; Southwell et al., 2017), subcortical responses may be less sensitive. This suggests they may be more vulnerable to stimulus properties and tasks demands (Zhao et al., 2019).

We also found that the PDR mismatch response is positively predicted by unexpectedness of incoming notes (in line with electrophysiological studies (Omigie et al., 2013; Quiroga-martinez et al., 2019), but it seems not to be modulated by degree of musical expertise. Larger MMN responses have been shown for musicians in a range of studies examining electrophysiological correlates of expectancy violation in music (Koelsch, Schmidt, & Kansok, 2002b; Oechslin, Van De Ville, Lazeyras, Hauert, & James, 2013; Tervaniemi, Tupala, & Brattico, 2012). One possibility is that this reflects a ceiling effect whereby the rather salient deviants used here were relatively easy to detect (given their large interval departures away from the melodic contour). Future studies examining the PDR to more subtle differences in musical structure may be expected to show similar expertise effects to those reported in previous studies.

Finally, our results provide evidence of music's usefulness in investigating the neural mechanisms underlying processing of stimuli statistical properties in a common, highly structured, and ecologically valid type of auditory stimulus, as music. While our work here focused on pitch expectations, previous studies have shown that music-induced temporal expectations are also tracked by the PDR (Damsma & van Rijn, 2017). Future experiments could address, for example, how introducing rhythm to concurrent melodic lines may affect the PDR to unexpected events. Similarly, that music induced chills – high arousal physiological responses associated with subjective pleasure – are associated with increased PDR (Laeng et al., 2016) suggest a usefulness of music in examining the relationship between stimulus information theoretic properties and reward processing. Whilst the IDyOM model used here is only able to deal with monophonic MIDI music, the development of the model for polyphonic music is underway (https://psyarxiv.com/wgjyv/) and it is expected that the approach we take here will be beneficial in a wider range of contexts in future years. By showing that predictive uncertainty can be used to modulate prediction-error related arousal, our findings have implications for understanding the variety of forms listeners' aesthetic appreciation of music may take. However, considering, more generally, the tight coupling between the error-related norepinephrine system and the reward-seeking dopaminergic pathway (Laeng et al., 2016; Xing, Li, & Gao, 2016; Zatorre & Salimpoor, 2013), our results emphasize that measuring the PDR may be useful for investigating the reward value of information across a range of modalities and domains.

In sum, we show that pupillometry in the auditory domain can reliably track the effect of context uncertainty on responses to sudden environmental change and independently from overt behavioural

430 responses. Given the hypothesised interplay between cortical and subcortical mechanisms in precision
431 weighted anticipatory processing and prediction resetting, a first milestone is set towards the non-
432 invasive quantification of the subcortical components.

433

451 **References**

452 Alamia, A., VanRullen, R., Pasqualotto, E., Mouraux, A., & Zenon, A. (2019). Pupil-linked arousal
453   responds to unconscious surprisal. *The Journal of Neuroscience*, 3010–18.

454 Aston-Jones, G., & Cohen, J. D. (2005). An integrative theory of locus coeruleus-norepinephrine
455   function: Adaptive Gain and Optimal Performance. *Annual Review of Neuroscience*, *28*(1), 403–
456   450.

457 Barascud, N., Pearce, M., Griffiths, T., Friston, K., & Chait, M. (2016). Brain responses in humans
458   reveal ideal-observer-like sensitivity to complex acoustic patterns. *Proceedings of the National
459   Academy of Sciences*, *113*(5), E616-25.

460 Bianco, R., Novembre, G., Keller, P. E., Kim, S.-G., Scharf, F., Friederici, A. D., … Sammler, D. (2016).
461   Neural networks for harmonic structure in music perception and action. *NeuroImage*, *142*.

462 Bianco, R., Novembre, G., Keller, P. E., Seung-Goo, K., Scharf, F., Friederici, A. D., … Sammler, D.
463   (2016). Neural networks for harmonic structure in music perception and action. *NeuroImage*,
464   *142*, 454–464.

465 Bigand, E., & Poulin-Charronnat, B. (2006). Are we "experienced listeners"? A review of the musical

466   capacities that do not depend on formal musical training. *Cognition*, *100*(1), 100–130.

467   Carrus, E., Pearce, M. T., & Bhattacharya, J. (2013). Melodic pitch expectation interacts with neural
468   responses to syntactic but not semantic violations. *Cortex*, *49*(8), 2186–200.

469   Clark, A. (2013). Whatever next? Predictive brains, situated agents, and the future of cognitive
470   science. *The Behavioral and Brain Sciences*, *36*(3), 181–204.

471   Damsma, A., & van Rijn, H. (2017). Pupillary response indexes the metrical hierarchy of unattended
472   rhythmic violations. *Brain and Cognition*, *111*, 95–103.

473   Dayan, P., & Yu, A. J. (2006). Phasic norepinephrine: A neural interrupt signal for unexpected events.
474   *Network: Computation in Neural Systems*, *17*(4), 335–350.

475   Dean, R. T., & Pearce, M. T. (2016). Algorithmically-generated Corpora that use Serial Compositional
476   Principles Can Contribute to the Modeling of Sequential Pitch Structure in Non-tonal Music.
477   *Empirical Musicology Review*, *11*(1), 27.

478   Eerola, T., & Toiviainen, P. (2004). MIDI Toolbox: MATLAB Tools for Music Research. University of
479   Jyväskylä: Kopijyvä, Jyväskylä, Finland.

480   Fink, L. K., Hurley, B. K., Geng, J. J., & Janata, P. (2018). A linear oscillator model predicts dynamic
481   temporal attention and pupillary entrainment to rhythmic patterns. *Journal of Eye Movement*
482   *Research*, *11*(2), 12.

483   Friston, K. (2005). A theory of cortical responses. *Philosophical Transactions of the Royal Society of*
484   *London. Series B, Biological Sciences*, *360*(1456), 815–36.

485   Fujioka, T., Trainor, L. J., Ross, B., Kakigi, R., & Pantev, C. (2004). Musical training enhances automatic
486   encoding of melodic contour and interval structure. *Journal of Cognitive Neuroscience*, *16*(6),
487   1010–21.

488   Garrido, M. I., Kilner, J. M., Stephan, K. E., & Friston, K. J. (2009). The mismatch negativity: a review of
489   underlying mechanisms. *Clinical Neurophysiology : Official Journal of the International*
490   *Federation of Clinical Neurophysiology*, *120*(3), 453–63.

491   Garrido, M. I., Sahani, M., & Dolan, R. J. (2013). Outlier Responses Reflect Sensitivity to Statistical
492   Structure in the Human Brain. *PLoS Computational Biology*, *9*(3).

493   Hansen, N. C., & Pearce, M. T. (2014). Predictive uncertainty in auditory sequence processing.
494   *Frontiers in Psychology*, *5*, 1052.

495   Hsu, Y.-F., Le Bars, S., Hamalainen, J. A., & Waszak, F. (2015). Distinctive Representation of
496   Mispredicted and Unpredicted Prediction Errors in Human Electroencephalography. *Journal of*
497   *Neuroscience*, *35*(43), 14653–14660.

498   Huron, D. (2001). Tone and Voice: A Derivation of the Rules of Voice-Leading from Perceptual
499   Principles. *Music Perception*, *19*(1), 1–64.

500   Huron, D. (2006). *Sweet Anticipation : Music and the Psychology of Expectation by David Huron*. (M.
501   T. M. Press., Ed.), *Sweet Anticipation: Music and the Psychology of Expectation.* Cambridge.

502   Joshi, S., Li, Y., Kalwani, R. M., & Gold, J. I. (2016). Relationships between Pupil Diameter and
503   Neuronal Activity in the Locus Coeruleus, Colliculi, and Cingulate Cortex. *Neuron*, *89*(1), 221–
504   234.

505   Koelsch, S. (2016). Under the hood of statistical learning: A statistical MMN reflects the magnitude of
506   transitional probabilities in auditory sequences. *Scientific Reports*, (August 2015), 1–11.

507   Koelsch, S., Gunter, T. C., v. Cramon, D. Y., Zysset, S., Lohmann, G., & Friederici, A. D. (2002). Bach

Speaks: A Cortical "Language-Network" Serves the Processing of Music. *NeuroImage*, *17*(2), 956–966.

Koelsch, S., Schmidt, B.-H., & Kansok, J. (2002a). Effects of musical expertise on the early right anterior negativity: an event-related brain potential study. *Psychophysiology*, *39*(5), 657–63.

Koelsch, S., Schmidt, B. H., & Kansok, J. (2002b). Effects of musical expertise on the early right anterior negativity: An event-related brain potential study. *Psychophysiology*, *39*(5), 657–663.

Krumhansl, C. L. (2015). Statistic, structures and style in music. *Music Perception*, *33*(1), 20–31.

Laeng, B., Eidet, L. M., Sulutvedt, U., & Panksepp, J. (2016). Music chills: The eye pupil as a mirror to music's soul. *Consciousness and Cognition*, *44*, 161–178.

Laeng, B., Sirois, S., & Gredeback, G. (2012). Pupillometry: A Window to the Preconscious? *Perspectives on Psychological Science*, *7*(1), 18–27.

Levitin, D. J., & Tirovolas, A. K. (2009). Current advances in the cognitive neuroscience of music. *Annals of the New York Academy of Sciences*, *1156*, 211–231.

Liao, H. I., Yoneya, M., Kidani, S., Kashino, M., & Furukawa, S. (2016). Human pupillary dilation response to deviant auditory stimuli: Effects of stimulus properties and voluntary attention. *Frontiers in Neuroscience*, *10*(FEB).

Liao, H., Yoneya, M., Kashino, M., & Furukawa, S. (2018). Pupillary dilation response reflects surprising moments in music. *Journal of Eye Movement Research*, *11*(2), 1–13.

Maess, B., Koelsch, S., Gunter, T. C., & Friederici, A. D. (2001). Musical syntax is processed in Broca's area: an MEG study. *Nature Neuroscience*, *4*(5), 540–545.

Maris, E., & Oostenveld, R. (2007). Nonparametric statistical testing of EEG- and MEG-data. *Journal of Neuroscience Methods*, *164*, 177–190.

Marmel, F., Tillmann, B., & Delbé, C. (2010). Priming in melody perception: tracking down the strength of cognitive expectations. *Journal of Experimental Psychology. Human Perception and Performance*, *36*(4), 1016–1028.

Mathôt, S., Fabius, J., Van Heusden, E., & Van der Stigchel, S. (2018). Safe and sensible preprocessing and baseline correction of pupil-size data. *Behavior Research Methods*, *50*(1), 94–106.

Meyer, L. B. (2001). Music and emotion: Distinction and uncertainties. In *Music and emotion: Theory and research.* (pp. 341–360). Meyer, Leonard B.: Dept of Music, U Pennsylvania, 210 SO 34th St, Philadelphia, PA, US, 19104: Oxford University Press.

Miranda, R. A., & Ullman, M. T. (2007). Double dissociation between rules and memory in music: An event-related potential study. *NeuroImage*, *38*(2), 331–345.

Müllensiefen, D., Gingras, B., Musil, J., Stewart, L., Levitin, D., Hallam, S., … Winner, E. (2014). The Musicality of Non-Musicians: An Index for Assessing Musical Sophistication in the General Population. *PLoS ONE*, *9*(2), e89642.

Näätänen, R., Paavilainen, P., Rinne, T., & Alho, K. (2007). The mismatch negativity (MMN) in basic research of central auditory processing: A review. *Clinical Neurophysiology*, *118*(12), 2544–2590.

Narmour, E. (2015). Toward a unified theory of the I-R model (part 1): Parametrci scales and their analogically isomorphic structures. *Music Perception*, *33*(1), 32–69.

Oechslin, M. S., Van De Ville, D., Lazeyras, F., Hauert, C.-A., & James, C. E. (2013). Degree of musical expertise modulates higher order brain functioning. *Cerebral Cortex (New York, N.Y. : 1991)*,

550   *23*(9), 2213–24.

Omigie, D., Pearce, M., Lehongre, K., Hasboun, D., Navarro, V., Adam, C., & Samson, S. (2019).
551   Intracranial Recordings and Computational Modeling of Music Reveal the Time Course of
552   Prediction Error Signaling in Frontal and Temporal Cortices. *Journal of Cognitive Neuroscience*,
553   *31*(6), 855–873.

Omigie, D., Pearce, M. T., & Stewart, L. (2012). Tracking of pitch probabilities in congenital amusia.
555   *Neuropsychologia*, *50*(7), 1483–1493.

Omigie, D., Pearce, M. T., Williamson, V. J., & Stewart, L. (2013). Electrophysiological correlates of
557   melodic processing in congenital amusia. *Neuropsychologia*, *51*(9), 1749–1762.

Pearce, M.T. (2005). The Construction and Evaluation of Statistical Models of Melodic Structure in
559   Music Perception and Composition. *Dissertation*, (December), 267.

Pearce, M.T. (2018). Statistical learning and probabilistic prediction in music cognition: Mechanisms
561   of stylistic enculturation. *Annals of the New York Academy of Sciences*, *1423*, 378–395.

Pearce, M.T., Ruiz, M. H., Kapasi, S., Wiggins, G. a, & Bhattacharya, J. (2010). Unsupervised statistical
563   learning underpins computational, behavioural, and neural manifestations of musical
564   expectation. *NeuroImage*, *50*(1), 302–13.

Pearce, Marcus T, & Wiggins, G. a. (2006). Expectation in melody: the influence of context and
567   learning. *Music Perception*, *23*(45), 377–405.

Pearson, R. K., Neuvo, Y., Astola, J., & Gabbouj, M. (2016). Generalized Hampel Filters. *Eurasip
569   Journal on Advances in Signal Processing*, *2016*(1).

Quiroga-martinez, D. R., Hansen, N. C., Højlund, A., Pearce, M., Brattico, E., Vuust, P., & Quiroga-
571   martinez, D. R. (2019). Decomposing neural responses to melodic surprise in musicians and
572   non-musicians : evidence for a hierarchy of predictions in the auditory system, 1–26.

Ricardo Quiroga-Martinez, D. (2018). Precision-weighting of musical prediction error: Converging
574   neurophysiological and behavioral evidence, 1–24.

Rohrmeier, M., Rebuschat, P., & Cross, I. (2011). Incidental and online learning of melodic structure.
576   *Consciousness and Cognition*, *20*(2), 214–222.

Ross, S., & Hansen, N. C. (2016). Dissociating Prediction Failure: Considerations from Music
578   Perception. *Journal of Neuroscience*, *36*(11), 3103–3105.

Rubin, J., Ulanovsky, N., Nelken, I., & Tishby, N. (2016). The Representation of Prediction Error in
580   Auditory Cortex. *PLOS Computational Biology*, *12*(8), e1005058.

Sara, S. J. (2009). The locus coeruleus and noradrenergic modulation of cognition. *Nature Reviews.
582   Neuroscience*, *10*(3), 211–223.

Sohoglu, E., & Chait, M. (2016). Detecting and representing predictable structure during auditory
584   scene analysis. *ELife*, *5*(Se), 1–17.

Southwell, R., Baumann, A., Gal, C., Barascud, N., Friston, K., & Chait, M. (2017). Is predictability
586   salient? A study of attentional capture by auditory patterns. *Philosophical Transactions of the
587   Royal Society B: Biological Sciences*, *372*(1714).

Southwell, R., & Chait, M. (2018). Enhanced deviant responses in patterned relative to random sound
589   sequences. *Cortex*, *109*, 92–103.

Tervaniemi, M., Tupala, T., & Brattico, E. (2012). Expertise in folk music alters the brain processing of
591   Western harmony. *Annals of the New York Academy of Sciences*, *1252*(1), 147–151.

592 Tervaniemi, Mari. (2009). Musicians-Same or Different? *Annals of the New York Academy of Sciences*,
593   *1169*(1), 151–156.

594 Tillmann, B., Bharucha, J. J., & Bigand, E. (2000). Implicit learning of tonality: A self-organizing
595   approach. *Psychological Review*, *107*(4), 885–913.

596 Tillmann, B., Janata, P., & Bharucha, J. J. (2003). Activation of the inferior frontal cortex in musical
597   priming. *Cognitive Brain Research*, *16*(2), 145–161.

598 Tillmann, B., & Lebrun-Guillaud, G. (2006). Influence of tonal and temporal expectations on chord
599   processing and on completion judgments of chord sequences. *Psychological Research*, *70*(5),
600   345–58.

601 Troncoso, X. G., Macknik, S. L., & Martinez-Conde, S. (2008). Microsaccades counteract perceptual
602   filling-in. *Journal of Vision*, *8*(14), 15–15.

603 Vuust, P., Brattico, E., Seppänen, M., Näätänen, R., & Tervaniemi, M. (2012a). Practiced musical style
604   shapes auditory skills. *Annals of the New York Academy of Sciences*, *1252*(1), 139–146.

605 Vuust, P., Brattico, E., Seppänen, M., Näätänen, R., & Tervaniemi, M. (2012b). The sound of music:
606   Differentiating musicians using a fast, musical multi-feature mismatch negativity paradigm.
607   *Neuropsychologia*, *50*(7), 1432–1443.

608 Vuust, P., & Witek, M. a. G. (2014). Rhythmic complexity and predictive coding: a novel approach to
609   modeling rhythm and meter perception in music. *Frontiers in Psychology*, *5*, 1111.

610 Weiskrantz, L., Cowey, A., & Barbur, J. L. (1999). Differential pupillary constriction and awareness in
611   the absence of striate cortex. *Brain*, *122*(8), 1533–1538.

612 Wetzel, N., Buttelmann, D., Schieler, A., & Widmann, A. (2016). Infant and adult pupil dilation in
613   response to unexpected sounds. *Developmental Psychobiology*, *58*(3), 382–392.

614 Widmann, A., Schröger, E., & Wetzel, N. (2018). Emotion lies in the eye of the listener: Emotional
615   arousal to novel sounds is reflected in the sympathetic contribution to the pupil dilation
616   response and the P3. *Biological Psychology*, *133*(January), 10–17.

617 Xing, B., Li, Y. C., & Gao, W. J. (2016). Norepinephrine versus dopamine and their interaction in
618   modulating synaptic function in the prefrontal cortex. *Brain Research*, *1641*, 217–233.

619 Zatorre, R. J., & Salimpoor, V. N. (2013). From perception to pleasure: music and its neural
620   substrates. *Proceedings of the National Academy of Sciences*, *110*, 10430–7.

621 Zhao, S., Chait, M., Dick, F., Dayan, P., Furukawa, S., & Liao, H.-I. (2019). Pupil-linked phasic arousal
622   evoked by violation but not emergence of regularity within rapid sound sequences. *Nature*
623   *Communications*, *10*, 4030.

624

625