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Pattern Classification of Working Memory Networks Reveals Differential Effects of Methylphenidate, Atomoxetine, and Placebo in Healthy Volunteers

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Stimulant and non-stimulant drugs can reduce symptoms of attention deficit/hyperactivity disorder (ADHD). The stimulant drug methylphenidate (MPH) and the non-stimulant drug atomoxetine (ATX) are both widely used for ADHD treatment, but their differential effects on human brain function remain unclear. We combined event-related fMRI with multivariate pattern recognition to characterize the effects of MPH and ATX in healthy volunteers performing a rewarded working memory (WM) task. The effects of MPH and ATX on WM were strongly dependent on their behavioral context. During non-rewarded trials, only MPH could be discriminated from placebo (PLC), with MPH producing a similar activation pattern to reward. During rewarded trials both drugs produced the opposite effect to reward, that is, attenuating WM networks and enhancing task-related deactivations (TRDs) in regions consistent with the default mode network (DMN). The drugs could be directly discriminated during the delay component of rewarded trials: MPH produced greater activity in WM networks and ATX produced greater activity in the DMN. Our data provide evidence that: (1) MPH and ATX have prominent effects during rewarded WM in task-activated and -deactivated networks; (2) during the delay component of rewarded trials, MPH and ATX have opposing effects on activated and deactivated networks: MPH enhances TRDs more than ATX, whereas ATX attenuates WM networks more than MPH; and (3) MPH mimics reward during encoding. Thus, interactions between drug effects and motivational state are crucial in defining the effects of MPH and ATX.

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INTRODUCTION

Stimulant and non-stimulant medications that influence dopamine (DA) and noradrenaline (NA) neurotransmission can reduce symptoms of attention deficit/hyperactivity disorder (ADHD). The stimulant drug methylphenidate (MPH) has been shown to have consistently greater clinical efficacy than atomoxetine (ATX), a non-stimulant drug recently approved for the treatment of ADHD in the USA and Europe (Spencer *et al*, 1998; Michelson *et al*, 2001; Faraone *et al*, 2005; Kemner *et al*, 2005; Starr and Kemner, 2005; Newcorn *et al*, 2008). ATX nonetheless offers several potential advantages over MPH, including reduced abuse liability, reduced risk of motor side effects and as an alternative treatment for patients non-responsive to stimulants (Newcorn *et al*, 2008). However, the mechanisms underlying their differences on human brain function are unclear.

There is converging evidence that weakened prefrontal cortex (PFC) function underlies several of the hallmark deficits in ADHD (Arnsten, 2006). In particular, working memory (WM)-the ability to hold and manipulate information for future action-is impaired in ADHD (Martinussen et al, 2005; Willcutt et al, 2005) and has been strongly linked to the activity of the catecholamines (DA and NA) within the PFC (Brozoski et al, 1979; Arnsten and Goldman-Rakic, 1985). WM performance is also known to be improved with MPH (Elliott et al, 1997; Bedard et al, 2004; Mehta et al, 2004), currently understood as resulting from an increased efficiency of frontoparietal WM regions shown using PET neuroimaging studies (Mehta et al, 2000; Schweitzer et al, 2004). Studies in experimental animals suggest that ATX has a similar ability to improve WM function (Gamo et al, 2010), via effects on prefrontal cortical activity, although there are no comparative human neuroimaging studies of the effects of MPH and ATX on WM networks.

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Previous studies in experimental animals have indicated that: (1) MPH inhibits both DA and NA transporters (DAT and NAT, respectively; Seeman and Madras, 1998; Han and Gu, 2006); (2) ATX is a selective inhibitor of NAT (Wong *et al*, 1982; Bolden-Watson and Richelson, 1993); and (3) both drugs increase concentrations of DA and NA in the PFC, but only MPH increases DA in the striatum (Bymaster *et al*, 2002). However, the neural consequences of these differential actions in human beings and their implications for functional brain networks are currently unknown.

Theoretically, systemically administered MPH and ATX may differentially influence distributed brain regions due to localized effects at DAT and NAT sites (Ciliax et al, 1999; Schou et al, 2005) and consequent effects on connected brain areas, in addition to the differential effects on striatal catecholamine neurotransmission shown in rodents (Bymaster et al, 2002). Thus, differential effects of MPH and ATX may be distributed across multiple brain regions. Multivariate pattern recognition (PR) methods are sensitive to such spatially distributed information by making use of the correlation between brain voxels and afford substantially greater sensitivity than conventional mass-univariate analysis methods (Haynes and Rees, 2006; Kriegeskorte et al, 2006; Norman et al, 2006). Therefore, we combined event-related fMRI with a novel whole-brain PR analytic approach to characterize and discriminate acute effects of MPH and ATX in healthy volunteers performing a WM task. Although we expected reductions in PFC activity after MPH, this study represents the first attempt to: (1) examine the effects of ATX on WM networks and (2) test potential differences between prefrontal cortical and striatal activation following administration of MPH and ATX in humans.

Finally, recent literature suggests an important contribution of reward to the regulation of WM-related brain activity (Ichihara-Takeda *et al*, 2010). This accords with evidence that both reward and MPH have similar effects on sustained attention task performance in ADHD (Trommer *et al*, 1991; Andreou *et al*, 2007). Therefore, we also explored the role of reward on WM function, with a focus on determining its impact on our ability to discriminate MPH and ATX.

METHODS

Participant Recruitment and Data Acquisition

Fifteen healthy male university students and members of the general public (aged 20–39 years) were recruited by local advertisement and were scanned on three occasions. Participants were screened by interview and physical exam for previous or current medical, psychiatric, or neurological problems. Other exclusion criteria included any substance abuse history, smoking >5 cigarettes per day, and consuming the equivalent of >5 cups of coffee per day. Participants were trained on the WM task on the screening day and were asked to refrain from alcohol and caffeine containing products for 24 h before dosing. Participants provided written informed consent and the study was approved by South London Research Ethics Committee 3. On each scanning day, participants were screened for drugs of abuse and alcohol, and then each participant received an oral dose of MPH (30 mg), ATX (60 mg), or a placebo (PLC) according to a randomized, doubleblind Latin square design. Doses of MPH and ATX were chosen to approximately match doses used in clinical practice, and doses reported in the literature (eg, Gilbert *et al*, 2006).

Scanning was performed on a General Electric Signa HDx 3T scanner and was timed to coincide with the peak plasma concentration for MPH and ATX (Wargin *et al*, 1983; Sauer *et al*, 2005). Between 90 and 135 min post-dose, six resting state arterial spin labelling scans were acquired, which will be reported separately. Approximately 135 min post-dose, gradient-echo (GE) echoplanar imaging was used to acquire 450 whole-brain images while participants performed a WM task (TR = 2 s, TE = 30 ms, FA = 75°, 38 3-mm-thick near-axial slices with 0.3 mm gap, in-plane resolution = 3.75×3.75 mm). A high-resolution GE structural scan was also acquired for each participant to assist accurate registration to a standard space (TR = 3 s, TE = 30 ms, FA = 90°, 43 3-mm-thick near-axial slices with 0.3 mm gap, in-plane resolution = 1.88×1.88 mm).

WM Task

During the WM task, 40 trials were presented with an intertrial interval of 8 or 10s, and during each trial, participants were required to remember the spatial location of a target stimulus (a dot) relative to a fixation cross. The task allowed each WM component process (encoding, delay, and retrieval) to be separately coded (Figure 1). Half the trials carried a monetary reward, indicated by the color of the stimulus and the order of trials was randomized and counterbalanced across participants. During encoding (2s), the target stimulus was presented, followed immediately by a mask to disrupt visual iconic memory. After a variable length delay (7 or 9s), the target and an additional distractor stimulus were presented and participants indicated which of the stimuli matched the target location by left or right button press on a two-button response box (retrieval). At the conclusion of the trial, feedback was provided, indicating success or failure and accuracy and response time (RT) were recorded. Acquisition was optimized for volume-based PR, with stimuli presented in a TR-locked manner, which ensures that data vectors were sampled from approximately the same point on the hemodynamic response curve and helps to generate a consistent response pattern for each trial. The task was written in VB.net, presented via projector to a screen at the end of the scanner bed and viewed by participants through mirrors attached to the head coil. Participants completed a visual analog scale (VAS; Bond and Lader, 1974) at four time points during each visit to record their subjective experience, which contained 16 items that were later collapsed to reflect two subjective factors: 'alertness' and 'tranquility' (Herbert et al, 1976; Supplementary Material). Outside the scanner, VAS responses were measured with a ruler and inside the scanner a computerized VAS was administered where participants recorded their responses by moving a sliding cursor using the two-button response box.



Figure I Delayed match to location working memory (WM) task. Note that the only difference between rewarded and non-rewarded trials is the color of the stimulus.

FMRI Data Pre-processing

FMRI data were realigned, spatially normalized, and smoothed with an isotropic 8 mm Gaussian kernel using statistical parametric mapping software version 5 (SPM5) (www.fil.ion.ucl.ac. uk/spm). Additional pre-processing was performed in Matlab (www.mathworks.com), which consisted of linearly detrending the data and applying a whole-brain mask to select intracerebral voxels. Classifier samples were constructed by: (1) shifting the onset of each trial by one volume to accommodate the hemodynamic delay; (2) converting brain volumes acquired during each task component to vectors; and (3) averaging two (encoding, retrieval, and shorter delay) or three (longer delay) consecutive volumes from each WM component. We averaged at least two volumes for each WM component to accommodate the temporal blurring induced by the hemodynamic response and to ensure that we captured the peak of the hemodynamic response. Trials where each participant responded incorrectly were excluded and remaining trials were averaged to construct a single mean sample per participant (averaged over approximately 16 correct trials). We constructed classifier samples for the baseline condition by extracting and averaging two volumes during the fixation period between trials (6-8 s after the end of feedback).

Classifier Implementation

We used binary Gaussian process classifiers (GPCs; Rasmussen and Williams, 2006) to classify: (1) each WM component from baseline; (2) rewarded from non-rewarded trials; and (3) each drug condition (ATX, MPH or PLC) from one another. GPCs are kernel classifiers similar to support vector machines (SVMs) that have good performance for fMRI (Marquand *et al*, 2010b). The main advantage of GPCs over SVMs is that GPCs provide probabilistic predictions and estimates of predictive uncertainty. Theoretical background and implementation details for GPCs have been presented elsewhere (Rasmussen and Williams, 2006; Marquand *et al*, 2010b), but a brief description is provided in Supplementary Material. In this work, we use linear kernel GPCs that help prevent overfitting and allow direct extraction of the weight vector as an image.

Recursive Feature Elimination

We embedded all classifiers contrasting reward or drug state in a recursive feature elimination (RFE; Guyon et al, 2002), which is a backward elimination feature selection approach that aims to find a set of features (voxels) by iteratively removing the least informative features. RFE was originally developed for SVM (SVM-RFE), and has been applied to multiple fMRI studies (eg, De Martino et al, 2008; Formisano et al, 2008; Hanson and Halchenko, 2008), but here we adapt it to GPC ('GPC-RFE'; Marguand et al, 2010a). RFE starts by creating an 'active feature set', initially containing all cerebral voxels. A classifier is trained repeatedly on the active set and at each iteration features are ranked and a subset of the lowest ranking features is removed (2% of voxels), which continues until no features remain. Predictive performance is measured at each stage of feature removal on an independent sample, allowing an optimal number of features maximizing predictive performance to be selected (Supplementary Material). RFE is most commonly applied because it modestly increases accuracy, but here our main motivation was because it yields a spatially sparse multivariate map (akin to a thresholded statistical parametric map), which is essential to prevent falsely inferring a brain region is functionally important when in fact it is not. RFE is a principled approach to achieve this aim and is more appropriate than an arbitrary voxel-wise threshold because it: (1) validates the multivariate pattern against predictive accuracy; (2) accommodates the multivariate structure of the pattern; and (3) does not require specification of an arbitrary threshold level. We did not apply GPC-RFE to the classifiers contrasting task and baseline, because this is a trivial classification problem and the objective was only to define the brain activity pattern evoked by the task for which an unthresholded map is preferable, but for reference

purposes, we provide classification accuracy for wholebrain classifiers trained to discriminate between all experimental contexts (Supplementary Material).

Cross-Validation

RFE can be viewed as a model selection problem, where model complexity is determined by a single parameter (the number of features to retain), which must be set without using the test data set to avoid overfitting. To achieve this, we used nested leave-one-out cross-validation (LOO-CV), which uses a three-way split of the data to provide an unbiased estimate of generalization ability while also allowing unbiased parameter estimation. For each LOO-CV fold, we excluded all data for a single participant for the test set, then repeatedly repartitioned the remaining 14 participants into a validation set (one participant) and training set (13 participants). We selected the optimal number of features on the validation set before applying it to the test set.

Visualization of the Differential Activity Pattern

To visualize the differential activity patterns, we retrained each GPC-RFE classifier using all participants' data, for which the optimal number of features was the mean across all training folds. For this application, we are interested in knowing how brain activity differs between experimental classes rather than providing a representation of the decision boundary, so we did not visualize classifier weights, which is common in PR (Mourao-Miranda *et al*, 2005). Instead, we employed a mapping approach that enables direct visualization of the relative class distribution, where the coefficient scores at each voxel represent the relative difference between experimental classes in the context of the entire pattern (Marquand *et al*, 2010b; Supplementary Material).

RESULTS

Performance Measures

Repeated-measures ANOVA revealed that time (RT) did not differ between drugs ($F_{2,28} = 0.001$, p = 0.99), or between rewarded and non-rewarded trials ($F_{1,14} = 0.003$, p = 0.96), and there was no reward × drug interaction ($F_{2,28} = 0.47$, p = 0.63). Participants made fewer errors on rewarded relative to non-rewarded trials ($F_{1,14} = 11.54$, p < 0.01), but errors did not differ between drug conditions ($F_{2,28} = 0.12$, p = 0.89) and there was no reward × drug interaction ($F_{2,28} = 1.80$, p = 0.19). A summary of RT and accuracy is provided in Supplementary Table S1.

Subjective Measures

Several participants reported side effects to the administration of the drugs (eg, nausea, drowsiness), but these were mild in all cases and mostly resolved before discharge on the study day. Subjective factors of alertness and tranquility were investigated as potential confounds to any drug effect using an independent repeated-measures ANOVA for each factor. For alertness, there was no main effect of drug (F_{2,28=}0.59, p = 0.56), but a main effect of time point was observed (F_{1,14=}8.83, p = 0.01), whereby post-dose VAS scores were slightly lower than pre-dose scores across all drug conditions. No drug × time point interaction was found (F_{2,28=}0.21, p = 0.81). For tranquility, there was no main effect of drug (F_{2,28=}1.78, p = 0.19) or time point (F_{1,14=}0.02, p = 0.88) and no interaction effect (F_{2,28=}0.48, p = 0.62).

Task Networks

Whole-brain classifiers accurately discriminated each WM component process from baseline for all drug conditions (mean accuracy (SEM) of 18 classifiers: 97.61% (0.01); p < 0.01, binomial test). As noted, the magnitude of GPC coefficients at each voxel provides a measure of the relative difference in blood oxygen level-dependent (BOLD) activation between classes in the context of the entire discriminating pattern and the sign indicates ('favors') the class with greater mean activation (Marquand et al, 2010b). GPC distribution maps (Supplementary Figures S1 and S2) revealed a distributed network (pattern) favoring the task component processes, including bilateral intraparietal sulci (IPS; Brodmann area (BA) 7), middle frontal gyri (BA 9/46), and bilateral medial and inferior frontal gyri (BA 6 and 47, respectively) in addition to visual and motor cortical regions. The pattern favoring baseline (task-related deactivations-TRDs) included regions comprising the default mode network (DMN), that is, posterior cingulate cortex (PCC; BA 30), precuneus (BA 31), medial PFC (BA 9/10 and 32), and lateral parietal cortex (BA 39).

Classification of Reward

Classification accuracy for GPC-RFE classifiers discriminating between rewarded and non-rewarded trials exceeded chance (50%) for all WM component processes and across all three drug conditions, with the exception of the encoding component on MPH (mean (SEM) of six classifiers: 70.72% (0.04); Figure 2a). The pattern favored reward and encompassed both the WM networks and TRDs described above. Specifically, BOLD activity in lateral PFC, parietal regions, medial PFC, and PCC/precuneus was relatively increased (Figure 3; Supplementary Figure S2); in other words, the effect of reward was to attenuate TRDs and enhance activity in the WM network. TRDs were most prominently attenuated during encoding and delay components of the rewarded WM task, whereas visual and WM regions were most prominently enhanced during delay and retrieval components of the task (see Figure 3). In summary, reward produces a generalized increase in BOLD activity, including both task-related activations (which increase with reward) and TRDs (which are suppressed with reward).

Classification Accuracy for Drug Contrasts

For ATX *vs* PLC, classification accuracy exceeded chance for encoding, delay, and retrieval components of rewarded trials (p < 0.05), but not during any WM component for the non-rewarded trials (Figure 2b). For MPH *vs* PLC, accuracy exceeded chance during encoding, delay, and retrieval of rewarded trials and during encoding of non-rewarded trials

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Figure 2 Classification accuracy for Gaussian process classifier (GPC)-recursive feature elimination (RFE) classifiers for (a) rewarded vs non-rewarded trials, (b) atomoxetine (ATX) vs placebo (PLC), (c) methylphenidate (MPH) vs PLC, and (d) MPH vs ATX. Asterisks indicate results significantly different from chance, that is, 50% (p < 0.05, binomial test).



Figure 3 Gaussian process classifier (GPC)-recursive feature elimination (RFE) distribution maps for classifiers discriminating between rewarded and non-rewarded trials for each working memory (WM) component (placebo (PLC) arm). (a) Encoding, (b) delay, and (c) retrieval. Maps were rescaled such that the absolute maximum coefficient score was ± 1. The magnitude of Gaussian process classifier (GPC) coefficients provides a measure of the relative difference in BOLD activity between experimental classes (in the context of the entire pattern) and the sign favors the class with greater mean activity. A distributed pattern favoring reward can be observed that indicates: (1) reward increased activity throughout WM networks and across all WM component processes and (2) reward-attenuated task-related deactivation (TRDs) in default mode network (DMN) regions, which was especially prominent during encoding and delay.

(p < 0.05; Figure 2c). For MPH vs ATX, classification accuracy exceeded chance for the delay component of rewarded trials (p < 0.05; Figure 2d).

For all classifiers exceeding chance, RT data were used to explore putative relationships between classifier performance and behavior. No significant correlations between RT and GPC-RFE predictive probabilities were found. Note that correlations with performance accuracy were not appropriate because all participants were well trained and made only a small number of errors, and only correct trials were included in the image analysis.

Discriminating Pattern for ATX vs PLC (Rewarded Trials)

Maps derived from classifiers trained to discriminate ATX from PLC on rewarded trials (Figure 4) contained a distributed pattern favoring PLC that included WM networks and DMN; in other words, in the reward context, ATX attenuated BOLD activity in WM networks and enhanced TRDs. During encoding, the pattern favoring PLC included the DMN (medial PFC and PCC/precuneus) and WM networks (IPS and bilateral PFC—BA 9, 46, and 47). In



Figure 4 Gaussian process classifier (GPC)-recursive feature elimination (RFE) distribution maps for classifiers discriminating between atomoxetine (ATX) and placebo (PLC) conditions for each working memory (WM) component (rewarded trials). (a) Encoding, (b) delay, and (c) retrieval. A distributed pattern favoring PLC can be observed that indicates that in a rewarded context: (1) ATX attenuated activity throughout WM networks, which was most prominent during delay and retrieval and (2) ATX enhanced task-related deactivations (TRDs) in default mode network (DMN) regions across all WM component processes. The cerebellum was the only region favoring ATX and was only observed during encoding.



Figure 5 Gaussian process classifier (GPC)-recursive feature elimination (RFE) distribution maps for classifiers discriminating between methylphenidate (MPH) and placebo (PLC) for each working memory (WM) component (rewarded trials). (a) Encoding, (b) delay, and (c) retrieval. A distributed pattern favoring PLC can be observed that indicates that in a rewarded context: (1) MPH attenuated activity throughout WM networks, which was most prominent during delay and retrieval and (2) MPH enhanced task-related deactivation (TRDs) in default mode network (DMN) regions across all WM component processes. The only regions favoring MPH were found during encoding and included cerebellum and small regions of lateral PFC.

addition, small clusters weakly favoring ATX were observed in the cerebellum and lateral PFC during encoding. During delay and retrieval components, the pattern favoring PLC was most prominent in WM regions.

Discriminating Pattern for MPH vs PLC (Rewarded Trials)

Maps derived from classifiers trained to discriminate MPH from PLC on rewarded trials (Figure 5) contained a distributed pattern favoring PLC similar to that observed for ATX, which also encompassed WM and DMN regions. During encoding, the pattern favoring PLC was mostly localized to DMN regions, but during delay and retrieval, the PLC pattern additionally included clusters in WM, motor, and visual regions, and was most widespread during retrieval. The pattern favoring MPH was restricted to encoding and was localized mostly to the cerebellum and lateral PFC.

Discriminating Pattern for MPH vs PLC (Non-Rewarded Trials)

The map derived from the classifier trained to discriminate MPH from PLC during the encoding component of nonrewarded trials (Figure 6) contained a distributed pattern, this time favoring MPH, including DMN, WM (eg, IPS), and visual regions. Thus, in the absence of reward, MPH enhanced activity in WM networks and attenuated TRDs. Note that the map contrasting MPH and PLC shows a strong qualitative similarity to the one contrasting rewarded and



Figure 6 Gaussian process classifier (GPC)-recursive feature elimination (RFE) distribution maps for classifiers discriminating between methylphenidate (MPH) and placebo (PLC) for the encoding working memory (WM) component (non-rewarded trials). A distributed pattern favoring MPH can be observed that indicates that during encoding and in a non-rewarded context MPH enhanced activity in some WM regions and enhanced task-related deactivation (TRDs) in default mode network (DMN) regions.



Figure 7 Gaussian process classifier (GPC)-recursive feature elimination (RFE) distribution maps for classifiers discriminating between methylphenidate (MPH) and atomoxetine (ATX) for the delay component of rewarded trials. Distributed patterns of activity favoring both MPH and ATX can be observed that indicate that in a rewarded context: (1) MPH enhanced activity throughout working memory (WM) networks relative to ATX and (2) ATX enhanced task-related deactivation (TRDs) in default mode network (DMN) regions.

Table I Summary of Classification Results

Contrast	WM components exceeding chance	Neuronal effects	Figure(s)
Reward vs control	Encoding, delay and retrieval for all drug contrasts, except for encoding on MPH	Reward increased activity in WM networks and suppressed TRDs	Figure 3, Supplementary Figure S2
ATX vs PLC (rewarded trials)	Encoding, delay and retrieval	ATX decreased activity in WM networks and enhanced TRDs	Figure 4
ATX vs PLC (non-rewarded trials)	None		Supplementary Figure S3
MPH vs PLC (rewarded trials)	Encoding, delay and retrieval	MPH decreased activity in WM networks and enhanced TRDs	Figure 5
MPH vs PLC (non-rewarded trials)	Encoding only	MPH increased activity in WM networks and suppressed TRDs	Figure 6
MPH vs ATX (rewarded trials)	Delay only	MPH had greater activity in WM regions relative to ATX and ATX resulted in greater TRDs	Figure 7
MPH vs ATX (non-rewarded trials)	None	_	

non-rewarded trials in the encoding component of the PLC condition (Figure 3a).

Discriminating Pattern for MPH vs ATX (Rewarded Trials)

The map derived from the classifier trained to discriminate MPH from ATX on the delay component of rewarded trials (Figure 7) contained distributed patterns favoring MPH and ATX. The pattern favoring MPH was mainly localized to WM regions (IPS and lateral PFC—BA 9/46) and the pattern favoring ATX was mainly localized to the DMN. Thus, during the delay component of rewarded trials, MPH relative to ATX resulted in greater BOLD activity in WM networks, and ATX relative to MPH resulted in greater TRDs.

For all contrasts, the differential patterns derived from GPC-RFE show a reasonably good correspondence to those derived from an equivalent univariate SPM, except the SPM retained substantially fewer voxels (at p < 0.001, uncor-

rected for multiple comparisons) than were retained by the classifier (data not shown).

A concise summary of the results is provided in Table 1.

DISCUSSION

We have shown differential effects of MPH and ATX on brain activity patterns in healthy volunteers performing a rewarded WM task. An important conclusion from our results is that the effects of MPH and ATX on WM are context-dependent. In the rewarded context, both MPH and ATX could be accurately discriminated from PLC across all task components, showing similar patterns of attenuation across the WM networks and enhanced TRDs. During the encoding component of non-rewarded trials, MPH, but not ATX, could be discriminated from PLC; MPH increased activity in WM regions and attenuated TRDs compared with PLC. The pattern of BOLD signal changes observed during the delay component of rewarded trials also discriminated MPH from ATX. In this context, and relative to ATX, MPH produced a pattern of increased activity in WM networks, whereas ATX produced greater activity in the DMN. Overall this complex set of findings suggests that: (1) both MPH and ATX have salient effects during rewarded WM in both task-activated and deactivated networks; (2) during the delay component of rewarded trials, MPH and ATX had opposing effects on activated and deactivated networks; and (3) MPH may mimic reward during encoding.

The results in this study were determined by applying recently developed PR techniques to the neuroimaging data, which afford substantially greater sensitivity than conventional mass-univariate techniques (Havnes and Rees, 2006; Norman et al, 2006) by making use of spatial correlation between voxels, lending themselves well to whole-brain inference. These properties make PR ideally suited to drug discrimination studies, where drugs administered systemically can theoretically influence distributed brain regions owing to direct effects at target receptor sites and consequent effects on connected brain regions. It is important to emphasize that multivariate brain maps derived from PR analysis provide a different perspective to mass-univariate analysis and should be interpreted differently. In particular, multivariate brain maps describe a pattern of activity, and coefficients should not be interpreted as representing focal effects because many brain regions potentially contribute to the accuracy of the classifier.

The WM networks identified in this study agree well with previous studies (Curtis *et al*, 2004; Gibbs and D'Esposito, 2005) and were sensitive to reward. During rewarded trials participants performed the task more accurately, which was reflected as a generalized pattern of increased brain activity throughout WM networks and in the DMN. Indeed, increased activity in WM brain regions is a known effect of reward on WM tasks (Pochon *et al*, 2002; Taylor *et al*, 2004; Pessoa and Engelmann, 2010) and may reflect an increase in neuronal effort.

MPH and ATX did not alter performance accuracy or response latency during the WM task. However, previous studies using MPH and amphetamine have suggested that reductions in BOLD activation accompanied by equivalent behavioral performance reflect an increased efficiency of WM networks (Mattay et al, 2000; Mehta et al, 2000). Thus, for our data in a rewarded context, this would seem to be the most parsimonious explanation for the effects of MPH and ATX on task activation and deactivation networks. This effect is probably mediated by increased catecholamine concentrations in WM regions (Bymaster et al, 2002), which is known to focus neuronal activity by enhancing responses to task-relevant stimuli while suppressing background noise (Foote et al, 1975; Seamans et al, 2001). Historically, DA has been linked with WM performance through increasing the efficiency of PFC neurons by decreasing delay-related response to 'noise' (Arnsten, 2007; Vijayraghavan et al, 2007) and the stabilization of their sustained activity (Durstewitz et al, 2000). However, NA is probably also important as therapeutic doses of MPH increase PFC extracellular concentrations of NA substantially more than DA (Berridge et al, 2006), and the beneficial effects of MPH and ATX on WM can be blocked by either DA D1 or NA $\alpha 2$ receptor antagonists (Arnsten and Dudley, 2005; Gamo *et al*, 2010). NA is also known to increase delay-related activity of PFC neurons in response to 'signals' (Arnsten, 2007) and increase the salience of novel stimuli, leading to the suggestion that it serves as an alarm system for contextual changes (Yu and Dayan, 2005).

The PCC, precuneus, and ventromedial PFC are known to show decreased activity during a wide range of goaldirected tasks (Shulman et al, 1997). These regions have been proposed to underlie a 'default mode' of brain function (Raichle et al, 2001) and it is thought that to facilitate goal-directed action, task-irrelevant mental activity in these regions must be suppressed. Indeed, failure to suppress default mode activity reflects momentary lapses in attention (Weissman et al, 2006), resulting in increased probability of error (Eichele et al, 2008). There is also preliminary evidence that ADHD may be characterized by deficiencies in attentional focus and insufficient suppression of brain activity in focal regions of the DMN (Fassbender et al, 2009) and that MPH may normalize the amplitude of TRDs in treatment-responsive ADHD participants (Peterson et al, 2009). Our results are consistent with this interpretation and further show that suppression of task-irrelevant mental activity may be a mechanism common to both MPH and ATX. Importantly, this effect was context-dependent, as it was only observed during rewarded trials.

In a rewarded context, classification accuracy was equivalent for classifiers discriminating MPH or ATX from PLC for each WM component, although accuracy was slightly higher for both drugs during retrieval relative to encoding and delay. Qualitatively, the effects of MPH and ATX were comparable, with both drugs producing a generalized decrease in brain activity in WM networks and DMN (ie, attenuation of activity in WM networks and enhancement of TRDs). Nonetheless, the extent of these effects separated the drugs during the delay component of rewarded trials: ATX attenuated BOLD activity in WM networks more than MPH and MPH enhanced TRDs more than ATX.

Microdialysis studies in rodents have shown that MPH and ATX increase DA concentration in the PFC, but only MPH increases DA in the striatum (Bymaster et al, 2002), and that therapeutic doses of MPH increase catecholamine concentration in the PFC substantially more than that in the striatum (Berridge et al, 2006). However, in our study we did not observe increased striatal activity following MPH, similar to other neuroimaging studies in healthy volunteers (Mehta et al, 2000; Udo de Haes et al, 2007). This may be because the WM task we employed does not substantially engage the striatum, even for rewarded trials (Supplementary Figure S2), which is consistent with a recent review of the effects of reward on WM (Pessoa and Engelmann, 2010) or simply because the consequential effects of MPH on striatal DA levels are expressed in connected brain regions. Thus, subcortical effects of MPH on DA remain a candidate mechanism for the differential effects of MPH and ATX, as the PFC and striatum are strongly connected by parallel corticostriatal circuits (Alexander et al, 1986), and there is emerging evidence suggesting that the striatal DA system plays a role in the modulation of the DMN (Kelly et al, 2009;

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Tomasi *et al*, 2009). However, studies concurrently measuring striatal DA release and its functional consequences on brain activity are required to test this hypothesis explicitly.

In a non-rewarded context, it was only possible to discriminate MPH from PLC during encoding. In this case, the differential pattern (Figure 6) bears a strong qualitative resemblance to that differentiating rewarded from nonrewarded trials (Figure 3), suggesting that while MPH did not improve performance at the dose administered, MPH nevertheless mimics the reward effect. Discrimination accuracies for classifiers contrasting rewarded and nonrewarded trials were also consistently lower on MPH than on ATX or PLC and did not exceed chance for encoding, indicating that activity patterns discriminating reward and non-rewarded trials were less distinguishable on MPH (Figure 2a), which is consistent with the suggestion that MPH increases task salience (Volkow et al, 2004). This effect is probably mediated by DA, because a learned association between a cue and a reward results in increased phasic dopaminergic firing during cue presentation not reward delivery (Schultz et al, 1993) and increased dopaminergic firing, often followed by immediate depression, is also associated with stimuli that resemble the rewarded stimulus (Schultz and Romo, 1990). Catecholaminergic signalling has also been associated with an 'inverted-U' dose-response relationship in the PFC (Arnsten, 2006; Levy, 2009) with optimal PFC function at intermediate concentrations and too much or too little DA or NA resulting in impaired PFC function. Although speculative at this stage, such a relationship may underlie different contextual effects of MPH, where rewarded and non-rewarded contexts may engage curves with different optimal dosing. Also, we only administered one dose of each drug here, so it is possible that ATX shares the rewardemulating effect at a different dose, which could additionally account for the classifier's inability to discriminate MPH and ATX during encoding of non-rewarded trials (Supplementary Figure S4).

Individual differences in response to drug administration may be an interesting line of future research. In particular, genetic factors influence responses to stimulants (Mattay et al, 2003), and although we did not collect genetic information here, inclusion of genetic factors can only be expected to improve predictive performance. As noted, only one dose of each drug was administered so that dose effects cannot be excluded as confounds, but three lines of evidence speak against this possibility: first, administered doses were matched according to doses used in clinical practice. Second, motor-evoked potentials were altered to a similar extent for both drugs using identical doses to those administered here (Gilbert et al, 2006). Third, opposing effects of MPH and ATX on activated and deactivated task networks during the delay component of rewarded trials are difficult to explain by a simple dose effect.

In summary, we accurately discriminated the effects of MPH and ATX on rewarded and non-rewarded WM networks using multivariate PR. We suggest that this method is ideal for drug discrimination studies because for most psychotropic medications subtle distributed effects probably predominate over strong focal effects. More importantly, our results show that MPH and ATX have effects on WM function that are context-dependent and 1245

suggest that the interaction between drug effects and motivational state will be crucial in defining the beneficial effects of MPH and ATX in ADHD.

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DISCLOSURE

The authors declare no conflict of interest.

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