

Reverberation Mapping in Bulk with OzDES RM

A Statistical Approach to Measuring the Geometry
of Active Galactic Nuclei with Light Echoes

By

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**Australian
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Declaration

This thesis is an account of my research, undertaken between August 2016 and September 2020 at the Research School of Astronomy and Astrophysics, College of Science, The Australian National University, Canberra, Australia.

Except where acknowledged in the customary manner, the material presented in this thesis is, to the best of my knowledge, original and has not been submitted in whole or part for a degree in any university.

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Abstract

Active galactic nuclei (AGN) are among the most luminous objects known to humans, and are ubiquitous in the local and distant Universe. It is widely accepted they host a supermassive black hole in their centre, however, the surroundings of the supermassive black holes are unknown due to a combination of the relatively small scales of these regions, and the spatial resolution limits of current instruments. The method of reverberation mapping (RM) aims to bypass these limitations and infer central AGN geometry through the analysis of light-echoes within these regions. By studying the light-signals emerging at different locations within the nuclei at different times, RM can provide insight to the structure of AGN.

In this thesis we investigate RM in bulk, or industrial scale RM, a relatively unexplored area becoming more relevant with the use of multi-object spectrographs for RM programs, which allows monitoring of a significantly higher number of AGN than previously. RM in bulk applies statistical methods to combine data from multiple sources to achieve high-quality results when the outcomes of individual sources are sub-par. We investigate this methodology using simulated mock data, and apply it to observations made by the Australian Dark Energy Survey Reverberation Mapping (OzDES RM) program. We find what appears to be a discrepancy between the results of simulated and observed data, which could suggest that current models used for mock data generation need improvement. Additionally, we examine the survey strategy of OzDES RM and its impact on achieving reliable RM results, and demonstrate that previous simulations may have underestimated the problems of the adopted strategies. Based on our results, we argue that a deeper analysis of the models used for our simulations is needed, to ensure more robust predictions about RM results. Furthermore, we recommend future RM programs reassess their survey strategies to secure high-quality results for the advancement of the field, and the applications thereof.

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To Dilyar
Without you, this wouldn't have been possible

1

Introduction

Probing the Universe with radio telescopes brought on the discovery of a new category of objects, namely quasars, or quasi-stellar objects (QSOs). These objects had the radio signature of galaxies, but a stellar, point-like appearance. Their spectra, however, did not resemble any known stars. It was only with time that quasars were recognised as distant, high-redshift sources ([Schmidt 1963](#)), and they have been among the most distant objects in the observable Universe ever since (*e.g.* [Warren & Hewett 1990](#); [Pentericci *et al.* 2002](#); [Bañados *et al.* 2018](#)). Over time, QSOs have been accepted as a subcategory of a wider class of objects, namely active galactic nuclei (AGN). AGN are generally high luminosity sources, and important objects of study in a range of fields within astronomy – they are observed at both low and high redshifts, at all wavelengths of the electromagnetic spectrum, for the purpose of understanding their internal structure, and for their impact on galaxy evolution (see *e.g.* [Kewley *et al.* 2006](#); [Kormendy & Ho 2013](#); [Netzer 2015](#); [Blandford, Meier & Readhead 2019](#)). AGN are also at the heart of this thesis, which examines a statistical approach to the investigation of the innermost, central regions of AGN through a method known as reverberation mapping (RM). Such analysis is important to our understanding of AGN themselves, and is further motivated by future applications of this methodology in distance measurements, and black hole and galaxy evolution.

1.1 Active Galactic Nuclei

Active galactic nuclei (AGN) are the luminous central regions – or nuclei – of a small percentage of galaxies. According to the unified model, proposed by [Antonucci \(1993\)](#) and [Urry & Padovani](#)

(1995) and presented in Fig. 1.1, a supermassive black hole (SMBH) is to be found at the centre of each AGN. Surrounding the black hole (BH) is an accretion disc, whose black-body radiation peaks at ultraviolet wavelengths. The luminosities arising from the accretion discs of AGN span at least six orders of magnitude from $L \sim 10^8 L_\odot$ to $L \sim 10^{14} L_\odot$ (see *e.g.* Shemmer *et al.* 2004; Ryden & Peterson 2010; Grier *et al.* 2013a; Wolf *et al.* 2018), and can thus be comparable to, and in many cases exceed, the luminosity of the remaining galaxy.

Going outward from the SMBH, the unified model outlines the existence of jets for the radio-loud portion of AGN. While the physics behind AGN jets is not yet fully understood, it is believed these phenomena originate close above the accretion disc (Blandford & Begelman 1999). A spinning BH with a strongly magnetised accretion disc can create electromagnetic currents which cause the ionised gas to be ripped away and spiral out from the SMBH (Blandford & Payne 1982). Jets are known to exist on scales ranging from astronomical units to megaparsecs, and can be observed at wavelengths ranging from radio to gamma-scales (Blandford, Meier & Readhead 2019). It should be noted that radio-loudness is not observed for all AGN, and is as such not a necessary defining factor.

Surrounding the SMBH with its accretion disc is the broad-line region (BLR). The particles here are partially ionised, and under strong gravitational influence by the central SMBH (Netzer 1977; Peterson 1993; Peterson & Wandel 2000). The absorption of the dense stream of photons

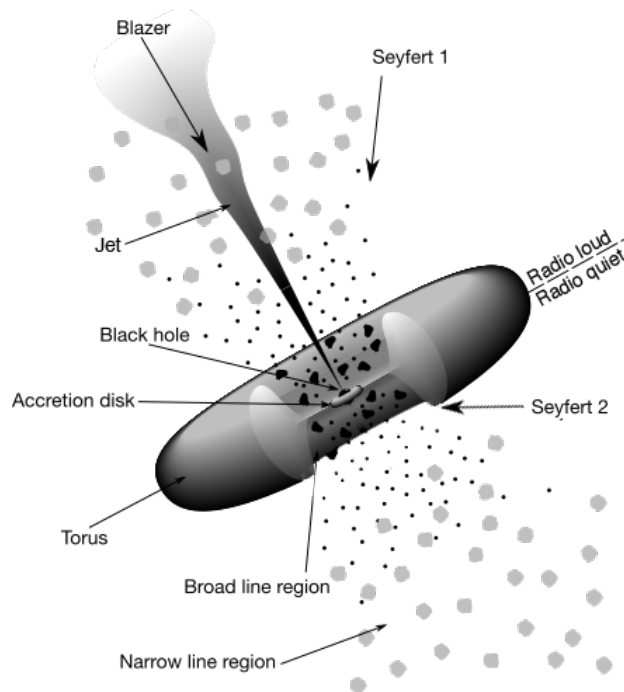


FIGURE 1.1: Illustration of the unified model of AGN, showcasing the different elements of an AGN, as well as demonstrating how the same physical phenomenon can lead to radically different observations depending on viewing angle. We note the existence of additional subclasses of AGN, which depend for instance on specific intensity at various part of the electromagnetic spectrum. Image adapted from Urry & Padovani (1995).

coming from the accretion disc is followed by a rapid re-emission, visible through the emission-lines corresponding to the ions present. The gravitational potential causes the individual BLR clouds to orbit the SMBH at high velocities, resulting in the clouds having individual Doppler shifts caused by the velocity components along our line of sight. The BLR is on sub-parsec scales, and is thus generally too small to be observed directly (a single observation of BLR scales has recently been performed in radio frequencies by [Gravity Collaboration et al. 2018](#)). The inability to resolve the individual clouds results in an observation of the collective composite of the individual Doppler shifts of the gas clouds. This composite causes strong broadening of the emission-lines, thus giving the BLR its name. While observations indicate an ionisation stratification of the BLR based on measurements of different time-lags for different emission-lines within the same AGN (see e.g. [Binette & Raga 1990](#); [Peterson et al. 1990](#); [Koratkar & MacAlpine 1992](#), for early measurements), finding the true geometry of the BLR is still at the heart of the RM field (see e.g. [De Rosa et al. 2018](#), and further discussion in Sec. 1.2).

Continuing outwards from the AGN centre, the radiation intensity will eventually decrease to an extent where graphite particles can survive, at a distance known as the dust sublimation radius ([Barvainis 1987](#); [Kishimoto et al. 2007](#)). The presence of graphite is important to the unified model, as the particles obscure the central regions of the AGN from certain angles. The dust sublimation radius, located at sub-parsec scales from the SMBH, marks the inner boundary of the obscuring, or dusty, torus, which reaches out to scales up to ~ 100 pc in size. The traditional unified model assumes the torus to be a single, toroidal, and smooth dust distribution. However, recent modelling and infrared observations suggest the existence of clumpy clouds, and other alternative geometries with multi-component structures ([Khim & Yi 2017](#); [Hönig 2019](#)).

Starting at scales similar to the torus, but extending up to kiloparsec distances, we find the narrow-line region (NLR, [Groves 2007](#)). The NLR is often presented as cone-shaped, although the geometry of this region is under investigation, with observations pointing towards leakage of radiation resembling that of the NLR through the torus ([Storchi Bergmann 2015](#)). The gas in the NLR is the interstellar medium, close enough to the SMBH to become ionised, but without the strong gravitational influence experienced in the BLR. The lower velocities, together with low gas densities, allow for the presence of forbidden lines – emission-lines which are suppressed due to their low transition probability (and hence extended life-time) compared to collisional de-excitation rates in denser environments. Unlike the BLR, the emission-lines from the NLR show little variation over time, and can thus be used for internal flux-calibration in RM context ([Peterson 2014](#)).

An important aspect of the unified model as presented by [Antonucci \(1993\)](#) and [Urry & Padovani \(1995\)](#) is that different parts of the AGN are seen depending on the inclination angle of the AGN relative to the observer, thus providing a simple, succinct explanation to a variety of different galaxies. Fig. 1.1 shows how a single AGN can be seen as a Seyfert 1, Seyfert 2, or blazar galaxy, depending on the location of the observer. Further galaxy classifications can be made based on the luminosity of the AGN and its parts. Seyfert galaxies and quasars, for instance, have been widely accepted to be the same underlying phenomenon on a continuous scale of luminosity, only initially

thought to be different phenomena due to a small number of observations of extreme case objects (Weedman 1976; Peterson 1997). For the purposes of RM and its applications we only make use of type 1 Seyfert galaxies and quasars, because a direct view of the BLR is crucial to the foundation of the RM method.

1.2 Reverberation Mapping

Midway through the previous century astronomers started investigating luminous targets with variable luminosity. Assuming that the objects contained a central, ionising source, they would be surrounded by a space completely ionised to an ionisation state dependent on the intensity of the ionising source, and the distance to it. With such an assumption it was expected that the luminosity variation originating at the centre would be echoed in the ionised region through the emission-lines corresponding to the given ionisation state. As such, the study of reverberation signals in sources with variable luminosity could infer their spatial properties, which were unresolved at optical wavelengths. Bahcall, Kozlovsky & Salpeter (1972) were the first to investigate the correlation between continuum and emission-line variability for AGN, and attempt modelling of the central regions – the accretion disc and BLR – of AGN. The method of inferring spatial information based on the echoes between continuum and emission-line variability has suitably been named reverberation mapping, RM, and we provide a simplified, schematic view of the principle of this method in Fig. 1.2. We note that an RM signal will be significantly more complicated in reality, and that geometric properties, such as the inclination of the BLR, will affect the way the continuum signal is perceived to be processed by the BLR by the observer (see *e.g.* Peterson 1993, 2014; Horne *et al.* 2004, for detailed overview of such reprocessing). An in-depth overview of realistic continuum and emission-line light-curves and their properties is given in Sec. 2.2.

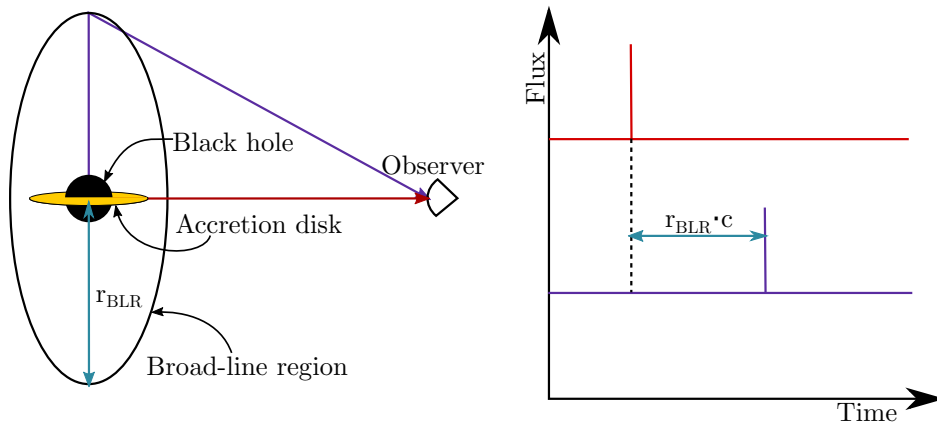


FIGURE 1.2: A schematic diagram of RM. A δ -function signal is emitted in all directions from the accretion disc surrounding the central SMBH. Some of the light is detected by a distant observer. Some light travels a distance r_{BLR} to the BLR, where it is reprocessed, and again emitted in all directions. The observer detects this signal as well. Due to small angle approximation, the additional distance travelled by the light is simply r_{BLR} , causing a time-delay of $r_{\text{BLR}} \cdot c$ between the detection of the original signal from the accretion disc, and the reprocessed signal from the BLR.

1.2.1 The Details of Reverberation Mapping

It is important to understand the relationship between continuum and emission-line light-curves, since they can be used to infer spatial information about the central regions of AGN. [Blandford & McKee \(1982\)](#) argued that the variation of the emission-lines could be expressed as a function of the continuum variability through a transfer-function $\Psi(t)$,

$$L(t) = \int_{-\infty}^{\infty} \Psi(t) C(t - \tau) d\tau, \quad (1.1)$$

where $L(t)$ and $C(t)$ are the emission-line and continuum light-curves at time t , respectively. The transfer-function is thus the BLR's emission-line response to a δ -function luminosity burst from the continuum source, and solving Eq. (1.1) for the transfer-function would allow one to infer the geometry of the system. While uncovering the full geometry of the BLR is a challenge even decades after it was first suggested (see *e.g.* [Skjelboe et al. 2015](#); [Xiao et al. 2018](#); [De Rosa et al. 2018](#); [Mangham et al. 2019](#)), we can uncover fragments of it by searching for the AGN time-lag τ_0 . This lag corresponds to the light-travel time between the continuum source to the BLR,

$$\tau_0 = r_{\text{BLR}}/c, \quad (1.2)$$

where r_{BLR} is the radius of the BLR, and c is the speed of light, as shown in Fig. 1.2. The recovery of this parameter is at the heart of RM, and has a number of different applications (see Sec. 1.2.2).

The method of RM, and the relationships outlined by Eqs. (1.1) and (1.2), are based on a small set of assumptions;

1. the continuum radiation is emitted by a compact, central source,
2. the light-travel time τ_0 is the most important time-scale in the system, and
3. there exists a simple, although not necessarily linear, relation between the observed and ionising continuum.

These assumptions have retroactively been shown to hold for RM systems ([Peterson & Horne 2004](#)). For the first point, the accretion disc has been found to be about two orders of magnitude smaller than the BLR. With regards to the light-travel time – or, simply, the AGN lag – there are two additional time-scales to be considered. It is important that the emission-line response to the continuum be considered instantaneous, and as such for the recombination time required for establishment of local ionisation equilibrium to be negligible. For particle densities found in the BLR the recombination time has been found to be on the order of minutes – significantly smaller than the days to months long AGN time-lags. The last time-scale to be considered is the cloud-crossing time, describing the amount of time the BLR structure can be considered stable. A conservative approach is to use the time-scale $r_{\text{BLR}}/\Delta v$, where Δv is the line-width of the emission-line, however, it is generally accepted that the cloud-crossing time can be ignored, as the light-travel time will exceed

the cloud-crossing time by a factor of $c/\Delta v$. Finally, observations of the luminosity variability at UV and optical wavelengths show a great correlation, implying the validity of using the optical continuum as a proxy for the ionising continuum (Kilerci Eser *et al.* 2015).

1.2.2 Applications of Reverberation Mapping

The time-lag τ_0 of an AGN may seem like a small and insignificant parameter, however, as suggested in Sec. 1.2.1, it has a variety of applications. Recovery of lags for a single AGN using a number of different emission-lines produces a range of different time-lags, consistent with ionisation stratification of the BLR (*e.g.* Peterson *et al.* 1990; Peterson 1993). The principle of RM can also be extended to what is known as continuum RM, which allows for measurements of the accretion disc (Mudd *et al.* 2018; Yu *et al.* 2020). For continuum RM, emission-line observation is unnecessary – instead the continuum region is observed through a range of broad-band filters, and relative lags are estimated between the multi-band light-curves. These time-lags provide relative size information, and upper limits of accretion disc size. Assuming a thin-disc model (Lynden-Bell 1969; Shakura & Sunyaev 1973), further size constraints can be made. In addition to providing BLR and accretion disc information, however, RM is also beneficial in the advancement of other fields, described in the following sections.

1.2.2.1 Growth and Evolution of Black Holes and Galaxies

Assuming the BLR is gravitationally bound to the central source, RM can be paired with the virial theorem to provide an estimate of mass M_{BH} of the SMBH;

$$M_{\text{BH}} = f \frac{r_{\text{BLR}} (\Delta v)^2}{G}. \quad (1.3)$$

Here f is a dimensionless scaling factor, Δv is the velocity dispersion of the emission-line used to find r_{BLR} , and G is the gravitational constant. The scaling factor f encompasses unknown BLR geometry and kinematics, and is widely accepted to be of order unity (*e.g.* Onken *et al.* 2004; Woo *et al.* 2010, 2015; Goad, Korista & Ruff 2012; Grier *et al.* 2013a). Given a basis of high-quality RM results, the time-intensive nature of RM can be omitted for BH mass measurements. Based on photoionisation equilibrium models it is expected that

$$r_{\text{BLR}} \propto \sqrt{L_{\text{AGN}}} \quad (1.4)$$

for the BLR size and AGN luminosity (Peterson 1988). Given this radius-luminosity ($r - L$) relationship single epoch spectroscopic BH masses can be calculated.

Estimating the masses of the central SMBHs for a variety of different galaxies over a range of redshifts is important to our understanding of the evolution of BHs and their host galaxies. SMBH masses have been found to correlate with properties of (the bulges of) their host galaxies (*e.g.* Magorrian *et al.* 1998; Ferrarese & Merritt 2000; Gebhardt *et al.* 2000a), and while they do not

necessarily influence each other, they must evolve together (Kormendy & Ho 2013). Understanding galaxy evolution improves our understanding of star formation through cosmological time, and thus also provides insight into the history of our existence (*e.g.* Kewley *et al.* 2006; Cattaneo *et al.* 2009; Heckman & Best 2014).

In nearby galaxies BH mass estimation is possible through a range of different methods. Direct BH mass measurements based on spatially resolved kinematics, while possible (Davies *et al.* 2006; Onken *et al.* 2014), are extremely limited due to insufficient spatial resolution with current technology. Sophisticated dynamical modelling has provided another method of BH mass estimation (Pancoast, Brewer & Treu 2014; Williams *et al.* 2018). Perhaps the best-known method is the $M_{\text{BH}} - \sigma_*$ relation, describing the relationship between BH mass and stellar velocity dispersion (*e.g.* Ferrarese & Merritt 2000; Gebhardt *et al.* 2000a). The $M_{\text{BH}} - \sigma_*$ relation has been measured for active (*e.g.* Grier *et al.* 2017a) and quiescent (*e.g.* McConnell & Ma 2013) galaxies alike, and used for calibration with Eq. (1.3) to establish an average value for the scaling factor f (Gebhardt *et al.* 2000b; Ferrarese *et al.* 2001). Due to differences in the $M_{\text{BH}} - \sigma_*$ relation between active and quiescent galaxies, the value of f has been found to differ, and consensus on best approach and scaling value has yet to be reached (see overview and discussion by Shankar *et al.* 2019).

The BH mass estimation methods applied to local galaxies prove to be challenging when the BH sphere of influence¹ cannot be resolved (Kormendy & Ho 2013). Application of RM allows to provide BH mass estimates for central SMBHs of dwarf galaxies and high-redshift galaxies where this resolution is a problem (Reines & Volonteri 2015; Schutte, Reines & Greene 2019). To ensure the masses are estimated correctly, calibration of Eq. (1.3) is necessary through the use of local galaxies.

1.2.2.2 Distance Measurements and Cosmology

By inverting the use of the $r - L$ relationship given by Eq. (1.4), RM can be applied to distance measurements. The luminosity L can be used with the relationship between flux and luminosity of an object,

$$F = \frac{L}{4\pi D_L^2}, \quad (1.5)$$

where F is the flux of the object, a measure of brightness at a (luminosity) distance D_L from the source. If the luminosity can be measured independently, through a process such as RM measurements and the $r - L$ relationship, the luminosity distance to the object can simply be inferred by inverting Eq. (1.5). Objects whose luminosity is known independent of its flux are known as standard candles, thus giving name to the method of inferring distance from the flux-luminosity relationship; the standard candle technique.

Distance measurements in space have been made since ancient Greece and Babylon (Heath &

¹The sphere of influence, $r_{\text{infl}} = GM_{\text{BH}}/\sigma_*^2$, of a SMBH corresponds to the region out to which the gravitational potential of the SMBH dominates over the gravitational field of the remainder of the host galaxy.

Samos 1913; Ryden & Peterson 2010), and continue their importance through a range of methods, including radar (Hughes 2001), RR Lyrae (Lee *et al.* 2014) and Cepheid variable stars (Leavitt & Pickering 1912; Macri 2017), masers (Herrnstein *et al.* 1999), type Ia supernovae (Branch & Tammann 1992), the Tully-Fisher (Tully & Fisher 1977) and Faber-Jackson relations (Faber & Jackson 1976), the fundamental plane (Djorgovski & Davis 1987), and baryon acoustic oscillations (Eisenstein *et al.* 2005), to mention some. The system of the various distance measurement methods at different scales in space is often referred to as the cosmic distance ladder, or extragalactic distance scale, and makes use of a wide variety of arguments and astrophysical phenomena. To ensure the stability of the distance ladder at higher rungs (greater distances), independent methods are used for cross-calibration. For example, Cepheid variable stars within the Milky Way can be used to anchor extragalactic Cepheids, which again can be used for distance measurements for supernova host galaxies (Riess *et al.* 2020). In a similar manner, different techniques spanning similar scales can verify distance measurements, solidifying the cosmic distance ladder.

The cosmic distance ladder is reaching its current limit with respect to distance – using individual objects and luminosity distance, at least – with type Ia supernovae (SNe Ia). A SN Ia is the result of a white dwarf star accumulating mass and reaching the Chandrasekhar limit (see *e.g.* Chandrasekhar 1931a,b; Mazzali *et al.* 2007), which causes a chain reaction of collapse, energy emission, and explosion. Because a SN Ia is achieved through slow mass accretion onto a white dwarf reaching its limit, SNe Ia explode at similar masses, and with approximately the same luminosity each time. Over time, methods have been developed to adjust for any deviations (Phillips 1993; Riess, Press & Kirshner 1996; Tripp 1998). Using SNe Ia high-quality distance measurements have been achieved for more than 1200 objects (see *e.g.* Abbott *et al.* 2019; Smith *et al.* 2020), yielding dependable distances corresponding to a look-back time of more than half of the age of the Universe. It is the use of SNe Ia distances that allowed for the discovery that our Universe is expanding at an accelerating rate (Riess *et al.* 1998; Perlmutter *et al.* 1999), leading to a Nobel Prize in Physics in 2011.

While SNe Ia clearly have been of extraordinary importance, the observing challenges and frequency of SN Ia events for redshifts $z > 1$ pose their use as standard candles an arduous task, with less than a dozen useful observations for $z > 1.5$ (Riess *et al.* 2018). SNe Ia leave a vast amount of space without reliable distance measurements. Given the transformation SNe Ia brought to the field of cosmology, it is natural to expect an extension of the standard candle technique to higher redshifts to improve our knowledge on cosmological questions. An extension of the extragalactic distance scale to higher redshifts would allow us to better study the deceleration phase during the matter-dominated stage of the Universe, and might provide insight into the characterisation and possible evolution of dark energy.

To extend the cosmic distance ladder with new standard candles, high luminosity objects or events are necessary. AGN and gamma-ray bursts (GRB) both fit this criterion, and have been observed at $z > 7.5$ (Bañados *et al.* 2018) and $z > 9$ (Cucchiara *et al.* 2011), respectively. Although effort has been made in establishing GRB as standard candles (*e.g.* Kodama *et al.* 2008; Dainotti

et al. 2013), they have the caveat that they are short-lived, transient events (often on orders of a second, up to orders of hours, Gendre *et al.* 2019; Li, Zhang & Yuan 2020), making them challenging to find. Meanwhile, AGN are constant sources of high luminosity, making pilot surveys and re-observations possible. Many attempts have been made to turn AGN into standard candles (*e.g.* Baldwin 1977; Elvis & Karovska 2002; Dai *et al.* 2012), most unsuccessful. It is only recently that Watson *et al.* (2011) showed that it may be possible to establish AGN as standard candles through RM by inverting the $r - L$ relationship, making them useful for distance measurements and cosmology applications.

1.3 Reverberation Mapping in the Past, Present, and Future

The first RM results were obtained for low-redshift Seyfert galaxies (*e.g.* Cherepashchuk & Lyutyi 1973; Gaskell & Sparke 1986; Peterson & Gaskell 1986), using hydrogen emission-lines. The AGN lags were found to be short – some on time-scales shorter than the observational frequency of the RM campaigns (Peterson 1988). Successful RM of higher redshift quasars was predicted to be time consuming for two reasons. The intrinsic luminosities of high redshift sources were expected to lead to longer time-lags, requiring longer RM campaigns for the lags to be recovered. This effect would be further exacerbated by cosmological time-dilation effects. A compilation by Bentz & Katz (2015) lists 62 AGN with RM results, of which 60 are at redshifts $z < 0.3$, and two are just above $z = 2$.

Only recently has the rate of RM results started increasing, mainly due to the use of multi-object spectrographs. RM programs utilising multi-object spectroscopy has so far been limited to the Sloan Digital Sky Survey Reverberation Mapping (SDSS-RM) program, targeting 849 AGN in the redshift range $0.1 < z < 4.5$, (*e.g.* Grier *et al.* 2017b, 2019) and the Australian Dark Energy Survey Reverberation Mapping (OzDES RM) program (to be discussed in Chap. 2), targeting 771 AGN at redshifts in the same redshift range. Multi-object spectrographs will, however, continue being used in the future – several RM programs making use of multi-object spectroscopy instruments are already planned. The Black Hole Mapper (BHM) survey is scheduled to start in the second half of 2020 as a part of the Sloan Digital Sky Survey, and will be targeting between 1000-1500 AGN for RM purposes at the same redshift range as SDSS-RM, with an expected outcome of ~ 1000 SMBH mass measurements (Kollmeier *et al.* 2017, 2019). The Time-Domain Extragalactic Survey Reverberation Mapping (TiDES-RM) program will use the 4-metre Multi-Object Spectroscopic Telescope (4MOST) with an intention to achieve distance measurements up to $z = 2.5$ by targeting 700 AGN in the redshift range $0.1 < z < 2.5$ on a fortnightly basis throughout the five half-year observing seasons (Swann *et al.* 2019). The Maunakea Spectroscopic Explorer is planning an extensive RM program, targeting ~ 5000 AGN at redshifts up to $z \sim 3$ for distance measurements, utilising ~ 100 epochs over a 3-5 year campaign (The MSE Science Team *et al.* 2019).

The use of multi-object spectroscopy in connection with RM has revolutionised the field not only by the number of AGN we simultaneously can observe, but also by the possibility of utilising statistical methods for RM analysis. Fine *et al.* (2012) explored the possibility of observing a

large number of sources to replace the need of frequent observations for RM. Basing their work on [Edelson & Krolik \(1988\)](#) they combine the data of sources whose lags could not be recovered individually to achieve a combined dataset from which a lag successfully can be recovered. The ability to apply statistical methods to maximise the use of data is of great importance given predictions of non-negligible failure rates for individual lag recovery (success rates of $\sim 35\text{--}45\%$ were predicted for OzDES RM by [King *et al.* 2015](#)). Given the time-intense nature of RM, the ability to successfully trade frequency of observations for number of sources would be a powerful tool for future RM programs. The work of [Fine *et al.* \(2012\)](#) has seen some application and improvement ([Fine *et al.* 2013](#); [Brewer & Elliott 2014](#); [Li *et al.* 2017](#)), however, it is still a fairly new and unexplored area within the field of RM.

In this work we study the outcomes of applying statistical methods to RM through simulations and observed data. We base our analysis around the OzDES RM program, and additionally expand our investigation to other hypothetical RM programs in order to provide insight for future planning of surveys. We present the outcome of a statistical analysis of OzDES RM data, highlight the limitations of simulations, and demonstrate the need of basic requirements for RM survey strategies.

1.4 Thesis Overview

This thesis is structured as follows. In Chap. 2 we provide an overview over the Dark Energy Survey (DES) and the Australian Dark Energy Survey (OzDES), detailing the properties of observations used for our observational data. Additionally, we outline the methods utilised for mock data generation, and AGN time-lag recovery. We apply the methods in Chap. 3, where we test and compare individual and stacked lag recovery on mock data. Using simulated data we define bins in redshift-luminosity parameter space dictating which AGN should be stacked together, and use this binning to perform stacked lag recovery for observed data. In Chap. 4 we investigate the impact of survey strategies on RM lag recovery results, and discuss the survey strategy choices of some current and future RM programs. We summarise our findings, draw conclusions, and present our recommendations for future RM research in Chap. 5.

Throughout we quote uncertainties at a 68% confidence level, and use magnitudes on the AB magnitude system. We follow [MacLeod *et al.* \(2010\)](#) in assuming a cosmology of $H_0 = 70 \text{ km s}^{-1} \text{ Mpc}^{-1}$, $\Omega_M = 0.30$, and $\Omega_\Lambda = 0.70$.

Although this thesis is written using the first person plural, the work presented throughout is my own, except where clearly referenced. The research was conducted primarily under the supervision of my two primary supervisors, Rob Sharp and Brad Tucker, with occasional input from additional collaborators.

2

Data and Methodology

Although the first reverberation mapping campaigns took place almost 50 years ago (Bahcall, Kozlovsky & Salpeter 1972), the field of RM has so far remained relatively small, and has only recently been introduced to multi-object spectroscopy. The current large-scale multi-object programs are SDSS-RM (Shen *et al.* 2015, 2016, 2019; Grier *et al.* 2017b, 2019) and OzDES RM (King *et al.* 2015; Hoormann *et al.* 2019), of which the latter is used as a baseline for simulations in this thesis. To ensure reliability of outcome, the methodology is developed through rigorous testing on mock data, based on empirical relations (MacLeod *et al.* 2010) and stochastic modelling of AGN light-curves (Kelly, Bechtold & Siemiginowska 2009). The analysis of light-curves is based on previous work by Fine *et al.* (2012, 2013), with minor adjustments to ensure applicability to OzDES RM data quality.

2.1 Observational Data

A successful RM campaign requires access to periodic monitoring of an AGN's central, ionising continuum, as well as observations of the BLR emission-lines (see Sec. 1.2). We obtain continuum measurements exclusively through photometric data derived from the Dark Energy Survey (DES). The emission-lines are monitored through spectroscopy observations by the Australian Dark Energy Survey (OzDES). Both programs are described in the following sections.

2.1.1 The Dark Energy Survey

The Dark Energy Survey (DES) Collaboration was established to provide a new instrument for the 4 m Blanco telescope at the Cerro Telolo Inter-American Observatory (CTIO) in Chile, shown on

the left hand side of Fig. 2.1, in exchange for up to 30% observing time over a five year period (The Dark Energy Survey Collaboration 2005; Dark Energy Survey Collaboration *et al.* 2016). The collaboration provided the Dark Energy Camera (DECam), a 570 megapixel CCD camera with a 2.7 deg^2 field of view (*e.g.* Flaugher 2005; Flaugher *et al.* 2015), the focal plane of which is shown on the right hand side of Fig. 2.1. DES was awarded a total of 525 nights of observation, distributed equally over five years (originally 2013–2018, Diehl *et al.* 2016). Official observations started in August 2013, following a science verification period a year prior, and ended in 2019, after an extension into the sixth year to achieve completion of the wide field survey, which was lacking due to bad weather conditions in the third year of observations (Diehl *et al.* 2018). DES delivered observations in five conventional broad-band filters – the g , r , i , z , and Y bands – spanning a 400–1065 nm wavelength range, and was conducted with two interleaved survey strategies; a wide survey targeting a 5000 deg^2 footprint visible from the Southern hemisphere at high galactic latitude, and a ten-field, deep time-domain survey (see *e.g.* Dark Energy Survey Collaboration *et al.* 2016, for a layout of both surveys).

DES was initially formed with an intention to study dark energy; specifically with the goal to determine the dark energy equation-of-state, and other important cosmological parameters. Four main survey elements were developed to provide a set of highly complementary studies of dark energy using diverse metrics – weak lensing, galaxy clusters, large-scale galaxy distribution, and SN Ia. The first three of these were studied through the wide field survey, whereas SN Ia made use of the smaller, but deeper, time-domain survey. A wide range of additional science cases were also developed to maximise the scientific impact of DES observations. An overview of the many fields of study within DES is provided by Dark Energy Survey Collaboration *et al.* (2016). The SN time-domain survey has been useful for other transient and variable sources, and the ~ 7 day cadence has proven useful to RM studies. Using photometry alone allows for RM within the accretion disc (Mudd *et al.* 2018; Yu *et al.* 2020), and given a spectroscopy extension to the DES deep field survey, a general RM program could be set up.

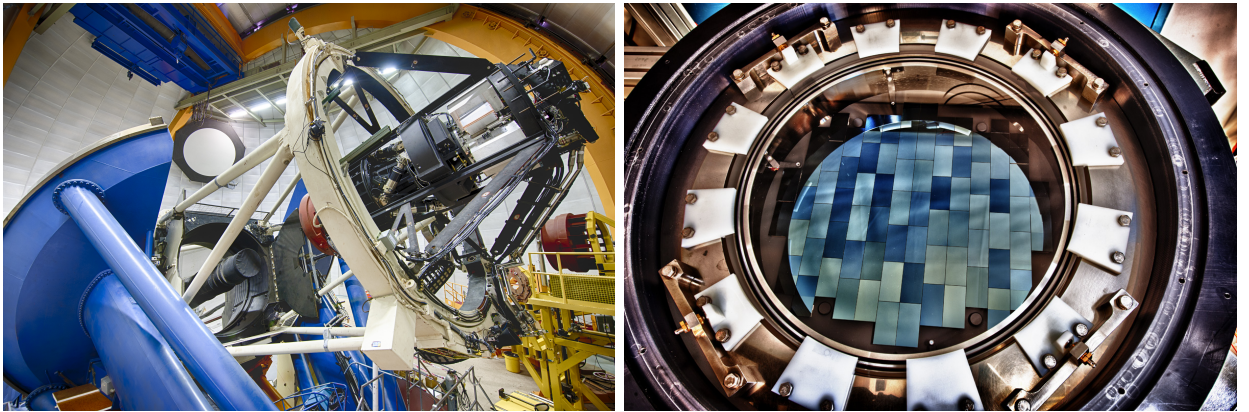


FIGURE 2.1: The Blanco telescope (left) at CTIO in Chile, and the focal plane of the DECam instrument (right) provided and used by DES. *Picture credit:* Reidar Hahn, Fermilab.

2.1.2 The Australian Dark Energy Survey (OzDES)

OzDES was established to provide spectroscopic follow-up for the DES SN fields to supply high accuracy redshifts for SN host galaxies (Yuan *et al.* 2015; Childress *et al.* 2017; Lidman *et al.* 2020). The survey was awarded a total of 100 nights, and ran over the same time period as DES, including a sixth season of observations. OzDES used the 3.9m Anglo-Australian Telescope (AAT) at Siding Spring Observatory (SSO) in Australia, utilising the AAOmega spectrograph (Sharp *et al.* 2006) and the 400 fibre two degree field facility (2dF, Lewis *et al.* 2002) fibre positioner. Both the telescope and the 2dF instrument are shown in Fig. 2.2. The dual-beam spectrograph was used with a 5700 Å dichroic, and 580V and 385R gratings, providing a wavelength coverage over the range $3700 \text{ Å} \leq \lambda \leq 8800 \text{ Å}$. Thanks to the 2 deg diameter field of view, OzDES was able to provide effective follow-up for DES, as illustrated by an overlap of the OzDES fibres and the 2dF field of view over a DES colour image of one of the SN fields in Fig. 2.3.

In addition to establishing SN host galaxy redshifts, OzDES has provided spectroscopic classification of transient events, as well as calibration of photometric redshifts. Repeated observations of the same areas of the sky have allowed monitoring of variable sources, and the measurements of redshifts for faint ($m_r \sim 25$ mag) sources by re-observation to build up sufficient signal (with up to two days of total integration times, Lidman *et al.* 2020). One of the fundamental design aspects of OzDES was the inclusion of “spare fibre” projects, allowing additional scientific research beyond the SN classification effort. The majority of fibres left over from the SN host observations were allocated to AGN to allow for an RM program. Known as OzDES RM, this joint DES and OzDES campaign since became one of the main goals of OzDES. A comprehensive overview of all scientific projects within OzDES, and the time and fibres assigned to them, is provided by Lidman *et al.* (2020).

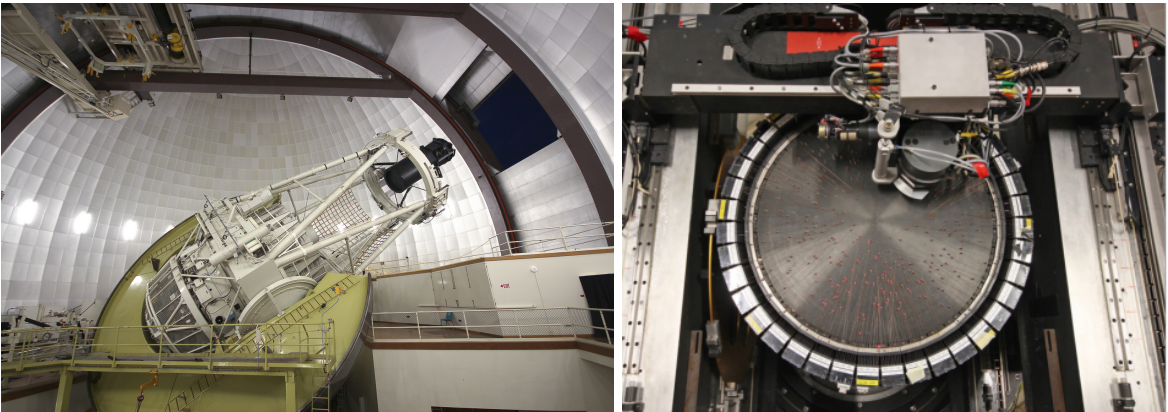


FIGURE 2.2: The telescope used by OzDES, the AAT (left) at SSO in Australia, and the 2dF instrument (right) in the process of placing fibres. Picture credit: Ángel R. López-Sánchez, Australian Astronomical Observatory/Macquarie University.

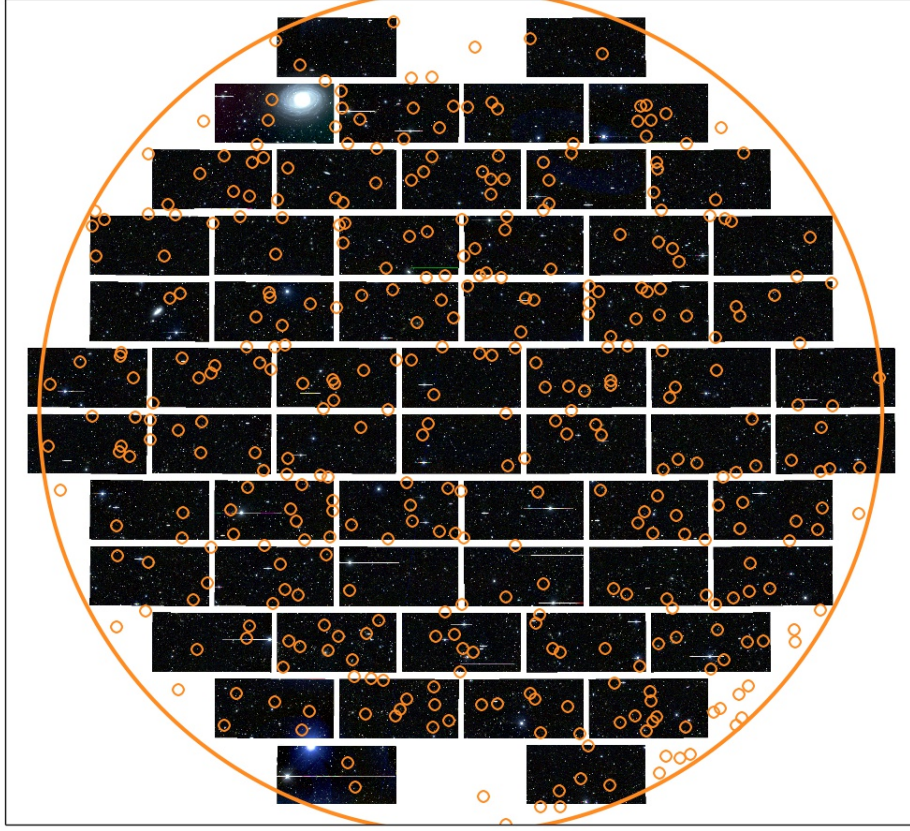


FIGURE 2.3: DES colour image of one of the SN fields overlaid by OzDES fibres (small circles) and the 2dF field of view (large circle). The similarity in field of view makes the OzDES follow-up for DES observations very efficient. Image credit: OzDES Collaboration.

2.1.3 The OzDES RM Program

The quasar catalogue used by OzDES RM was developed based on DES photometry, utilising a combination of point source, colour, and variability selection. The specific details regarding target selection are provided by [Tie *et al.* \(2017\)](#). Here we provide a brief summary of the methods used. Point source selection was made using DES weighted **SExtractor** ([Bertin & Arnouts 1996](#)) classifiers to identify point sources exclusively. The sources were colour selected using a combination of methods, including additional observations using the K band from the Vista Hemisphere Survey (VHS; [McMahon *et al.* 2013](#)), and the $W1$ and $W2$ bands from the Wide-Field Infrared Survey Explorer (WISE; [Wright *et al.* 2010](#)). Selections were made based on $W1 - W2$, $g - i$ versus $i - W1$, and $g - i$ versus $i - K$ colours, in addition to the probabilistically based **XDQSOz** software ([Bovy *et al.* 2012](#)). Finally, the variability selection used *griz* data to calculate a multi-band χ^2 variability statistic to discriminate variable sources from non-variable ones. The target selection was performed during the year of pre-pilot survey observations for OzDES, and contained initially 1263 AGN after spectroscopic confirmation by OzDES. The number has since been further reduced, by setting requirements for signal-to-noise ratio, excluding sources which fell between the inter-chips

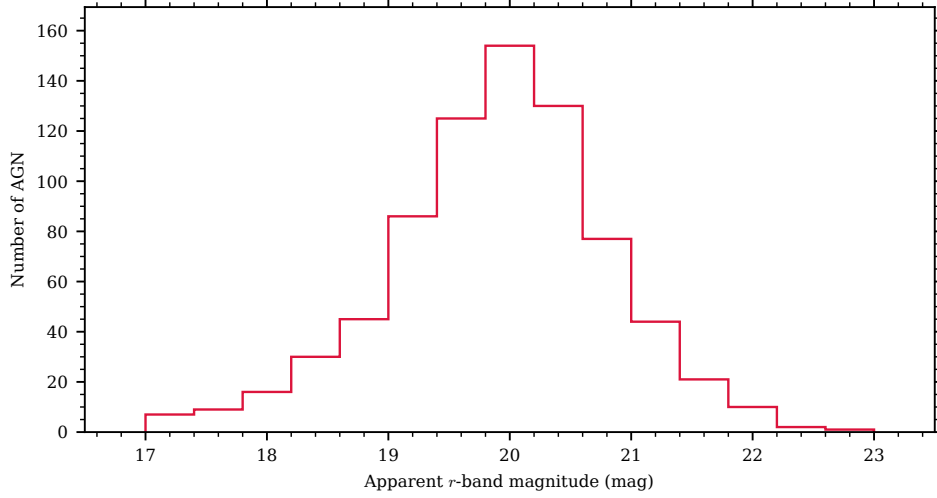


FIGURE 2.4: Distribution of the final OzDES RM targets by median apparent r -band magnitude.

of the DECam focal plane, or had their key broad emission-lines redshifted to undesirable parts of the spectrum. The final number of OzDES RM targets is 771 (see *e.g.* Mudd *et al.* 2018; Hoormann *et al.* 2019), which span the redshift interval $0.1 < z < 4.5$, and have magnitudes $17.0 \text{ mag} < m_r < 23.0 \text{ mag}$, their distribution by apparent r -band magnitude shown in Fig. 2.4. With the AAOmega spectrograph configured for OzDES observations, three prominent emission-lines can be used for RM for targets in the redshift interval spanned by OzDES RM AGN – $\text{H}\beta$, Mg II , and C IV . In Tab. 2.1 we divide our sample according to which emission-lines are present, and denote the associated redshift interval of each group.

The overarching goal of OzDES RM is to recover lags for as many AGN as possible within our sample, however this is beyond the scope of this work, which intends to apply the statistical method of Fine *et al.* (2012) to groups of similar AGN. As a proof of concept, we focus on a subsample of the OzDES RM AGN which can be evaluated together, leaving further analysis of other AGN to future work. Since different emission-lines have different $r - L$ relationships, we can only simultaneously evaluate AGN which are observed by the same emission-line. To maximise the outcome of the statistical approach to RM in this work (see Sec. 1.3, and Sec. 2.3.3 for a more comprehensive discussion), we choose to focus on an emission-line group of AGN with a high number of targets. The

TABLE 2.1: Overview of OzDES RM AGN in terms of sample size for different redshift ranges and emission-lines.

Redshift range	Emission-line(s)	Number of AGN
$z < 0.69$	$\text{H}\beta$	73
$0.69 \leq z < 0.74$	$\text{H}\beta$ & Mg II	11
$0.74 \leq z < 1.58$	Mg II	279
$1.58 \leq z < 1.94$	Mg II & C IV	181
$z \geq 1.94$	C IV	227

emission-line through which the highest number of AGN in the OzDES RM sample are observed is Mg II, however, this emission-line has known associated problems with iron subtraction (Vestergaard & Wilkes 2001). Without being able to correctly subtract the iron contribution of the emission line, the variations of the emission-line are likely to be reduced, thus complicating the lag estimation. We choose to focus on the C IV-line in this work to circumvent the added complications associated with the Mg II-line in early stage analysis of OzDES RM data, however, OzDES RM work on iron subtraction and calculation of lag estimates for the Mg II emission-line is already underway (Yu *et al.* 2021).

OzDES observing runs were scheduled at a monthly cadence during the half-year long observation seasons. The total number of spectroscopy epochs for any OzDES RM target is lower than the total number of observing runs due to nights lost to unfavourable weather, as well as the choice to combine observations from multiple nights within any single run. An example of the data acquired by OzDES is shown in Fig. 2.5, where we present all spectra available for object DES J022828.19-040044.30, one of the AGN studied for the purpose of RM with the C IV emission-line. The spectra are flux-calibrated, achieving $<5\%$ uncertainty at most wavelengths for the majority of the AGN. Reduced transmission and lowered quantum efficiency of detectors for blue wavelengths causes an increase of uncertainty at the bluest wavelengths, however, only up to $\sim 10\%$ uncertainty. The flux-calibration procedure, as well as a local continuum-subtraction to achieve emission-line light-curves, is described in detail by Hoormann *et al.* (2019). This process requires processed DES photometry, acquired through the DES Image Processing Pipeline, a part of the DES Data Management System (Morganson *et al.* 2018). The photometry calibration ensures high-quality continuum light-curves with associated uncertainties, which are generally at sub-percent levels (Burke *et al.* 2018).

The OzDES survey concluded observations in January 2019 with a total of 41 observing runs. An additional season has recently been scheduled for the second half of 2020, and will provide additional information for the AGN with longest time-lags, represented by the sources with high redshift and luminosity values. These supplemental observations will extend the baseline of the $r - L$ relationship. At the time of writing the spectroscopic observations are limited to five seasons due to a bottle-neck imposed on the OzDES calibration pipeline arising from the processing time of the DES photometric data. The average number of available spectroscopy epochs is currently 17, to be utilised with an average of 153 photometry epochs. In Fig. 2.6 we provide an example of observing, showing the dates of observation for object DES J024632.55-003439.10.

2.2 Simulations

To ensure a robust understanding of the systematic and statistical uncertainties in lag recoveries from OzDES observations, we create representative mock data on which we test our methodology. Some of this testing is similar to that presented by Fine *et al.* (2012), whose stacking methodology used for composite lag estimation this work is based upon. We turn to the literature to find empir-

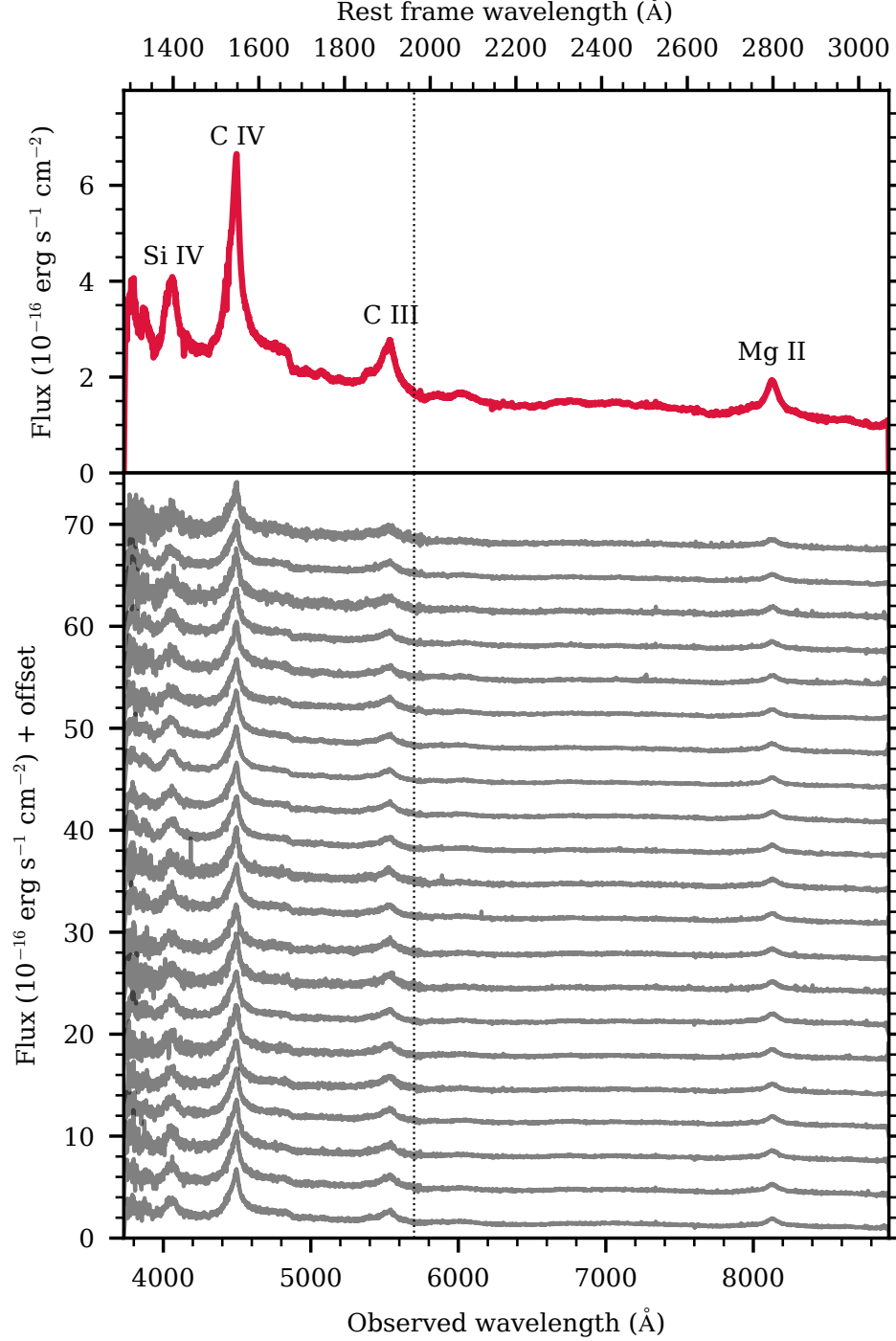


FIGURE 2.5: The OzDES spectra for DES J022828.19-040044.30, a $z = 1.9048$, $m_r = 18.12$ mag quasar. The top panel shows the co-added spectrum based on all available epochs, with each individual spectrum shown in the bottom panel. The vertical line corresponds to the dichroic split between the blue and red arm of the spectrograph, which have different spectral resolutions.

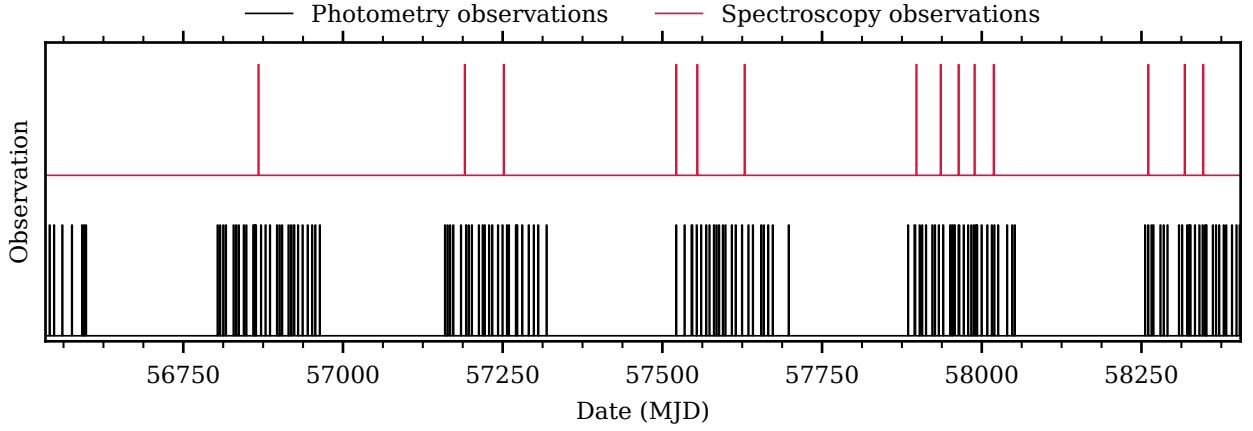


FIGURE 2.6: Time-line illustrating the DES photometry (black) and OzDES spectroscopy (red) observations of object DES J024632.55-003439.10, a $z = 1.7277$, $m_r = 19.54$ mag quasar. Each observation is marked by a vertical line extending from the horizontal baseline of each observation type.

ical relations between AGN light-curves and other AGN parameters, and consider both observing strategies and measurement uncertainties for OzDES as well as DES to ensure the mock data is representative of observations to the highest degree possible.

The redshifts of AGN imply a shift and stretching of the observed spectra. Due to the limited wavelength range of our broadband filters, we observe non-negligibly different fragments of the AGN spectra when targeting AGN at different redshifts. Any given apparent magnitude observed is thus not only a function of the intrinsic luminosity and distance of the object, but depends also on which fragment of the spectrum the broad-band filter measured. To achieve accurate luminosity estimates for our AGN, we apply a K-correction to the average magnitude of any AGN, utilising the DES filter response curves and the quasar spectrum template described by [Vanden Berk *et al.* \(2001\)](#).

When assessing our chosen lag recovery method, the most crucial thing to investigate is whether the chosen method can successfully recover the correct time-lag between two light-curves. We utilise mock continuum and emission-line light-curves, with a known lag between them, to test our recovery method. From Eq. (1.1) we know emission-line light-curves can be obtained from continuum light-curves given a transfer-function $\Psi(\tau)$, so we commence the generation of mock data with continuum light-curve construction. The continuum variability of AGN has been studied extensively since quasars were first discovered, and found to have power-spectra $P(f)$ at optical wavelengths consistent with $P(f) \propto 1/f^2$, corresponding to the power-spectra of autoregressive models ([Giveon *et al.* 1999](#); [Collier & Peterson 2001](#); [Czerny *et al.* 2003](#)). Perhaps the most known autoregressive model is the random walk, which is a special case of the first order autoregressive model. A variation of the random walk, namely the damped random walk (DRW), has been shown to be a statistically valid model for the optical continuum light-curves of AGN ([Kelly, Bechtold & Siemiginowska 2009, 2011](#); [Kozłowski *et al.* 2010](#)).

Generation of realistic mock continuum light-curves using the DRW model requires a definition of the key parameters. [Kelly, Bechtold & Siemiginowska \(2009\)](#) suggested a DRW model utilising

only three free parameters; a characteristic time-scale of variations, the amplitude of variations, and the average value of the light-curve around which the variations occur. We utilise observable information to establish the average light-curve value, and make use of the results of MacLeod *et al.* (2010) to establish appropriate values for the remaining parameters. To relate their work to previous quasar variability studies which utilised the structure function (SF, Simonetti, Cordes & Heeschen 1985), MacLeod *et al.* (2010) utilise the long-term variability amplitude parameter¹ SF_∞ and a damping time-scale² τ_d . Both parameters can be expressed on a functional form $f(\lambda_{\text{RF}}, M_i, M_{\text{BH}})$,

$$\log_{10} f = A + B \log_{10} \left(\frac{\lambda_{\text{RF}}}{4000 \text{ \AA}} \right) + C(M_i + 23) + D \log_{10} \left(\frac{M_{\text{BH}}}{10^9 M_\odot} \right), \quad (2.1)$$

where λ_{RF} is the rest frame wavelength for which the parameter is being calculated, M_i is the absolute magnitude through the i -band, and the coefficients for SF_∞ and τ_d are given separately in Tab. 2.2. MacLeod *et al.* (2010) also provide a distribution for the black hole mass M_{BH} , based only on M_i , through

$$p(\log_{10} M_{\text{BH}} | M_i) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left[-\frac{(\log_{10} M_{\text{BH}} - \mu)^2}{2\sigma^2} \right], \quad (2.2)$$

where $\mu = 2.0 - 0.27M_i$ and $\sigma = 0.58 + 0.11M_i$. By calculating separate parameter values for each of the emission-lines utilised for RM, and acquiring M_i values from observed m_r and z values through K-correction, we obtain all parameters necessary to model continuum light-curves through the DRW model.

We utilise the DRW to generate continuum light-curves in magnitude-space, by drawing each step of the DRW from a normal distribution whose mean and variance encompass information regarding the previous step of the DRW, and the overall properties of the light-curve. For any time t , the magnitude $m(t)$ is governed by the expectation value

$$E[m(t)|m(t - \Delta t)] = e^{-\Delta t/\tau_d} m(t - \Delta t) + \bar{m} (1 - e^{-\Delta t/\tau_d}), \quad (2.3)$$

TABLE 2.2: Coefficients to be used with Eq. (2.1) to calculate values for quasar variability parameters SF_∞ and τ_d (MacLeod *et al.* 2010).

Variable	A	B	C	D
SF_∞	-0.51	-0.479	0.131	0.18
τ_D	2.4	0.17	0.03	0.21

¹The long-term variability amplitude is defined for light-curves expressed in magnitude-space, where the light-curves fluctuate around a mean value. These fluctuations appear asymmetric when light-curves are presented in flux-space.

²MacLeod *et al.* (2010) call this parameter τ , however, we choose instead to represent it as τ_d to avoid confusion with the time-lag parameter.

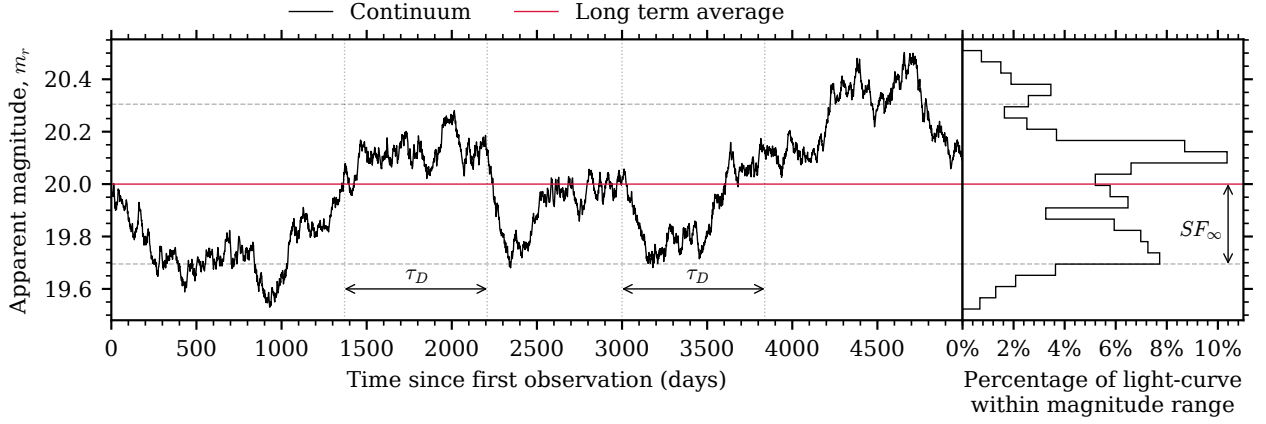


FIGURE 2.7: A mock continuum light-curve in magnitude-space (left plot) together with the histogram of the magnitudes which went into the light-curve (right plot). The three DRW parameters are illustrated on the light-curve and its histogram. The long term average shows the value around which the light-curve tends to fluctuate, and represents an approximate mean value of the histogram. The variability amplitude, SF_∞ , is an approximate standard deviation of the histogram. Finally, the damping time-scale, τ_d , is indicated twice across the mock light-curve to illustrate its match with some of the long-term variability of the light-curve.

and the variance

$$\text{Var}[m(t)|m(t - \Delta t)] = \frac{1}{2}SF_\infty^2(1 - e^{-2\Delta t/\tau_d}), \quad (2.4)$$

where $m(t - \Delta t)$ is the magnitude at a time Δt prior to time t , and $\bar{m}$ is the average magnitude of the light-curve. Fig. 2.7 shows an example of a mock continuum light-curve generated through this method. The DRW parameters τ_d and SF_∞ are indicated on the plot, the latter of which is demonstrated on a histogram of the continuum light-curve, to better reflect its proximity to the width of the distribution. Similarly, the time-scale τ_d is shown twice, to highlight its overlap with some of the larger structures of the light-curve. To finalise the mock continuum light-curve generation, we recast the continuum light-curves to flux to ensure they are in the same format as emission-line light-curves.

To generate a mock emission-line light-curve, we require a transfer-function with which a pre-existing continuum light-curve should be convolved. While the nature of the transfer-function remains to be uncovered and is likely to change from source to source (see discussion in Sec. 1.1), a top-hat (rectangular) transfer-function has been a common choice in the literature (Zu, Kochanek & Peterson 2011; Brewer & Elliott 2014; King *et al.* 2015). A top-hat transfer-function is given by

$$\Psi(t) = \begin{cases} \frac{A}{t_2 - t_1} & \text{for } t \in [t_1, t_2] \\ 0 & \text{otherwise,} \end{cases} \quad (2.5)$$

where A is a scaling factor, and it is a simple, yet conservative choice for a transfer-function, as it provides maximum amount of smoothing everywhere it is defined. The mean lag for this

transfer-function is $\tau_0 = \frac{1}{2}(t_1 + t_2)$, which we adopt as the AGN lag we try to recover. Following the work of [King *et al.* \(2015\)](#) we set the scaling term $A = 1$, and the edges of the top-hat function to be $t_1, t_2 = \pm 0.1 \cdot \tau_0$, such that the transfer-function is centred at the lag τ_0 and has a total width of 20% of the lag value. We convolve our mock continuum light-curves with transfer-functions on the form of Eq. (2.5) to achieve mock emission-line light-curves for our simulations. We present an example of a mock continuum light-curve and three emission-line light-curves generated from it through convolution with transfer-functions centred at different lags in Fig. 2.8, illustrating how our definition of the transfer-function results in a change in both transfer-functions and emission-line light-curves for different values of the AGN lag.

Convoluting Eq. (2.5) with mock continuum light-curves to achieve mock emission-line light-curves requires the value of the mock AGN lag to be set, and we can take advantage of current knowledge of $r - L$ relationships to ensure the light-curves are generated in a realistic way. The $r - L$ relationship has been studied extensively for the $H\beta$ -line ([Kaspi *et al.* 2000, 2007](#); [Bentz *et al.* 2009, 2013](#); [Fonseca Alvarez *et al.* 2019](#)), and effort has also been made to establish the $r - L$ relation for Mg II ([Trakhtenbrot & Netzer 2012](#); [Homayouni *et al.* 2020](#); [Zajaček *et al.* 2020](#)), however, given our decision to focus on the C IV emission-line (see discussion in Sec. 2.1.3) we generate our emission-line light-curves for the C IV-line. There have been a number of $r - L$ relationship estimates for the C IV-line ([Peterson *et al.* 2005](#); [Kaspi *et al.* 2007](#); [Lira *et al.* 2018](#); [Hoormann *et al.* 2019](#); [Grier *et al.* 2019](#)), and while the analysis of this thesis could have been performed using any of these relationships, the testing of multiple relationships is beyond the scope of this work. We have chosen to base our work on the $r - L$ relationship found by [Kaspi *et al.* \(2007\)](#), as it was the latest

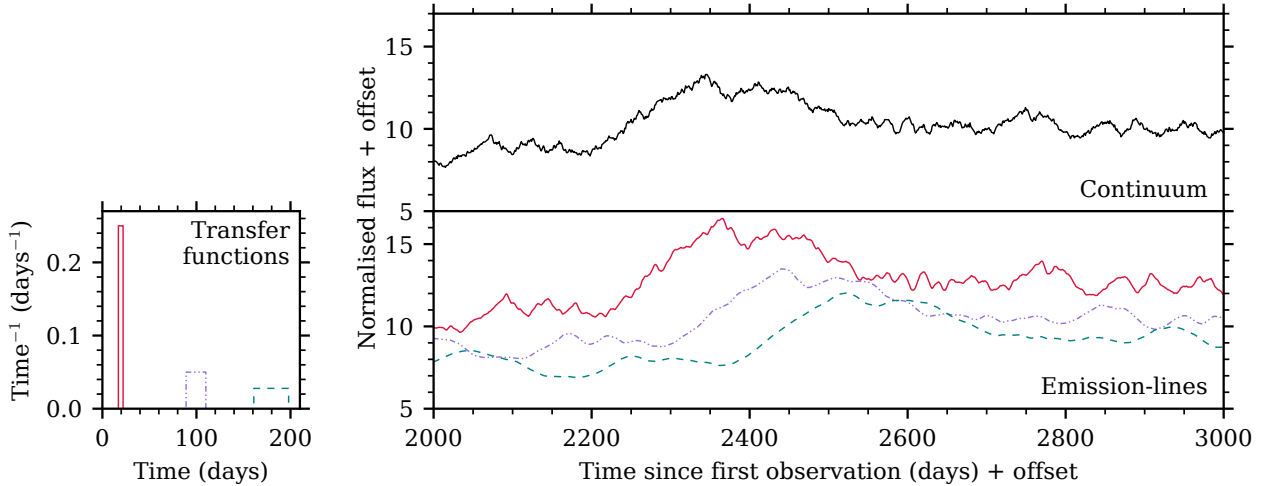


FIGURE 2.8: A mock continuum light-curve (top plot) together with emission-line light-curves (bottom right). Each emission-line light-curve is obtained by calculating a convolution of the continuum light-curve with the transfer-function (bottom left) represented with the same colour and line-style as the resulting emission-line. The top-hat function decreases in height and increases in width for higher values of the lag, causing stronger smoothing for emission-line light-curves with longer delays.

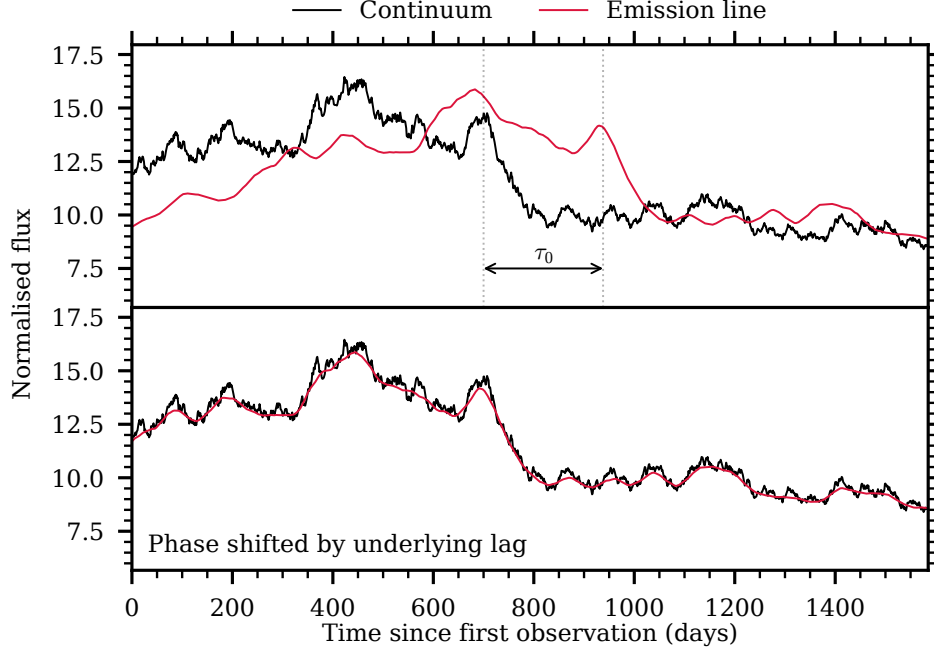


FIGURE 2.9: A pair of mock light-curves based on OzDES RM parameters. The emission-line light-curve is created with a smoothing and delay representative of what would be expected for an AGN with these parameters. The light-curves are quasi-continuous, and have no associated uncertainty or errors added, thus representing an idealistic observation of the AGN light-curves. The top panel shows the light-curves with the time-lag between them, indicated by a double arrow between two vertical lines. In the bottom panel we have shifted the emission-line light-curve backwards by the value of the time-lag to better observe the similarities between the light-curves.

available at the start of the analysis. The chosen $r - L$ relationship is given by

$$\frac{r_{\text{BLR}}}{10 \text{ light-days}} = (0.24 \pm 0.06) \left[\frac{\lambda L_{\lambda} (1350 \text{ \AA})}{10^{43} \text{ ergs s}^{-1}} \right]^{0.55 \pm 0.04}, \quad (2.6)$$

where L_{λ} is the spectral luminosity at wavelength λ , in this case $1350 \text{ \AA}$. A mock continuum light-curve is shown in Fig. 2.9, together with an emission-line light-curve based on an appropriate lag for the AGN whose underlying parameters were used to generate the continuum light-curve. In the top plot of Fig. 2.9 we present the light-curves as emitted by the AGN, with the time-lag τ_0 between the light-curves indicated by an arrow. In the bottom plot, we shift the emission-line light-curve backwards by τ_0 to highlight the good fit between the light-curves, as well as the differences between them.

The outline of mock light-curve generation so far produces an idealistic light-curve pair, described perfectly by the DRW and top-hat transfer-function, with no errors or uncertainties associated. The light-curves can be considered to represent the underlying light-curves as emitted by the mock AGN on which they are based. To achieve light-curves representative of observations, we modify the mock data by adding Gaussian noise and recording associated uncertainties. We base the value of the noise and uncertainty on a percentage of the average flux of the light-curve, using a 2% and

10% uncertainty for our continuum and emission-line light-curves, respectively, based on the true observational uncertainty (see Sec. 2.1.3). This choice of uncertainty provides conservative mock data to represent even the weakest of our sources.

Due to the random nature of the DRW model, a single set of AGN parameters can generate an infinite number of different light-curves, which may perform differently in the lag recovery process due to stochastic variations. To allow for testing of different window-functions without changing the light-curves and their associated properties, it is useful to keep the underlying light-curves the same, and change the sampling alone. We generate underlying mock light-curves identically spaced, with daily cadence in the observing frame, yielding quasi-continuous mock light-curves. Subsequently, we sample the underlying mock light-curves with our desired window-functions to obtain effective light-curves, which, together with the aforementioned uncertainty, correspond directly to the observed light-curves one could obtain through RM programs. We present a pair of effective light-curves, based on the survey strategies and uncertainties of OzDES RM, in Fig. 2.10. These light-curves are based on the underlying light-curves shown in Fig. 2.9, which we include in Fig. 2.10 at low opacity. The effective light-curves are given by the set of “measurements” shown in Fig. 2.10 as individual points with errorbars.

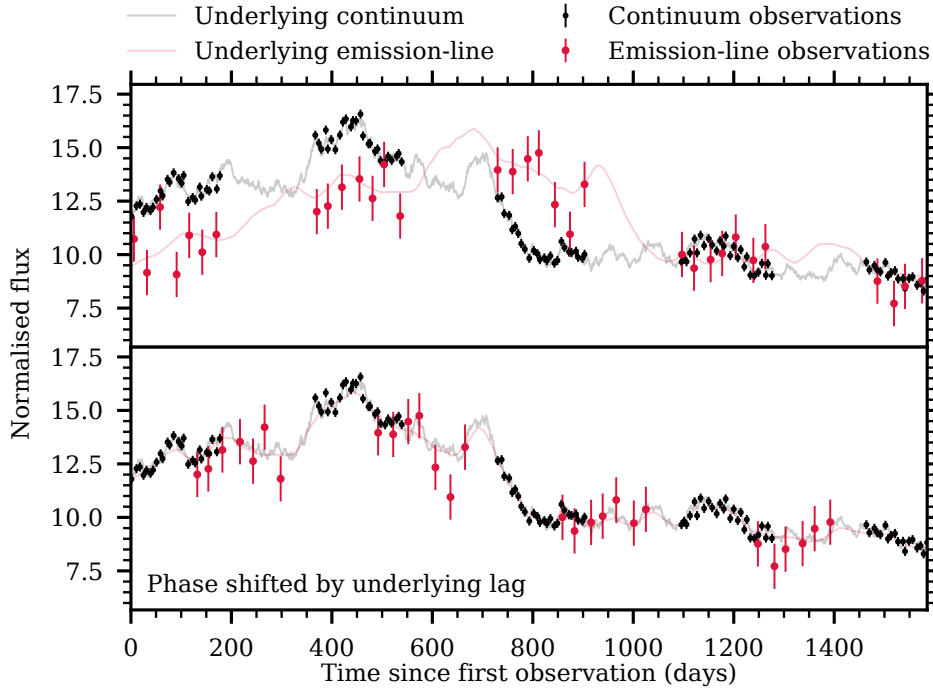


FIGURE 2.10: The same mock continuum and emission-line light-curves as in Fig. 2.9, however, in addition to the underlying, quasi-continuous light-curves (shown at low opacity), we include points representing the observations we might achieve with OzDES RM. It is clear that while the quasi-continuous light-curves match each other well, the similarity between the effective (“observed”) light-curves is significantly less obvious. It is a clear demonstration of the necessity of a robust lag recovery method.

2.3 Estimating the Lag Between Light-Curves

A number of different RM lag recovery methods have been developed since Bahcall, Kozlovsky & Salpeter (1972) first correlated the continuum and emission-line light-curves of AGN. The methods can be divided in two main groups: cross-correlation based, such as the interpolated cross-correlation function (ICCF, Gaskell & Sparke 1986; Gaskell & Peterson 1987), the discrete cross-correlation function (DCF, Edelson & Krolik 1988), the z -transformed discrete cross-correlation function (ZDCF, Alexander 1997); and Markov chain Monte Carlo (MCMC) based, such as JAVELIN (Just Another Vehicle for Estimating Lags In Nuclei, Zu, Kochanek & Peterson 2011), and CREAM (Continuum REverberation AGN MCMC, Starkey, Horne & Villforth 2016). The MCMC based methods have largely been found to be consistent with the cross-correlation based methods, and are often seen as preferable due to a combination of their smaller uncertainties and the more advanced modelling of light-curves between observations (*e.g.* Zu, Kochanek & Peterson 2011; Grier *et al.* 2012, 2013b; Starkey, Horne & Villforth 2016). While the cross-correlation based methods are believed to be conservative in their lag recovery, and often used as a sanity check for the more advanced methods, it is possible the uncertainties associated with the lag recoveries of the MCMC based methods are underestimated (Zu, Kochanek & Peterson 2011). Given the drawbacks of each methodology type, caution should be shown in all interpretation of results.

2.3.1 The Discrete Cross-Correlation Function

This thesis focuses on a statistical approach to RM, thus requiring a lag recovery method which allows effortless evaluation of multiple AGN simultaneously. The DCF, originally developed to combat the problem of computing correlation functions for irregularly sampled data, has already been proven to be applicable for simultaneous lag recovery for multiple objects, both in its transformed version (Li *et al.* 2017), and on its original form (Fine *et al.* 2012, 2013). While the more traditional method of the ICCF has been shown to be more successful (White & Peterson 1994), we chose to use the more conservative approach of the DCF for two reasons. First and foremost, it lends itself easily to performing lag recovery for bulk data. Secondly, the uncertainties of the DCF are better defined – comparatively, interpolation methods suffer additional implied uncertainty in co-variant error propagation. We defer the use of the MCMC based methods to future analysis, as it at this time is unclear how to correctly perform lag estimation for groups of objects with these methods.

Following Edelson & Krolik (1988), we calculate the DCF between two datasets a and b in a two step process. For the first step, we calculate all the pairwise lags $\Delta t_{ij} = t_j - t_i$, corresponding to the measuring times t_i and t_j for the measurements a_i and b_j , respectively. Additionally, we calculate the set of unbinned discrete correlations (UDCF),

$$\text{UDCF}_{ij} = \frac{1}{N}(a_i - \bar{a})(b_j - \bar{b}) \quad (2.7)$$

for all combinations the elements a_i and b_j of a and b , and their average values $\bar{a}$ and $\bar{b}$. The

variable N represents a normalising factor for the measurements of the deviations of the datasets from their means. We wish to normalise by the intrinsic width of the dataset, however, the observed width of the dataset will be broadened if the data have associated uncertainties. Assuming Gaussian uncertainties, the full width of a dataset is given by $\sigma_{\text{total}}^2 = \sigma_{\text{intrinsic}}^2 + \sigma_{\text{uncertainty}}^2$, yielding $\sigma_{\text{intrinsic};a,b}^2 = \sigma_{\text{total};a,b}^2 - \sigma_{\text{uncertainty};a,b}^2 \equiv \sigma_{a,b}^2 - e_{a,b}^2$. The normalisation factor $N = [(\sigma_a^2 - e_a^2)(\sigma_b^2 - e_b^2)]^{1/2}$ was adopted by [Edelson & Krolik \(1988\)](#). Due to the limited number of observational epochs and the size of the uncertainties for OzDES RM Data, we find it necessary to modify the original normalisation factor to better suit data of OzDES RM caliber. We adopt the normalisation factor

$$N = \begin{cases} [(\sigma_a^2 - e_a^2)(\sigma_b^2 - e_b^2)]^{1/2} & \text{where both } \sigma_{a,b} > e_{a,b}, \\ \sigma_{a,b} \sqrt{(\sigma_{b,a}^2 - e_{b,a}^2)} & \text{where } \sigma_{a,b} \leq e_{a,b}, \text{ but } \sigma_{b,a} > e_{b,a}, \text{ and} \\ \sigma_a \sigma_b & \text{where both } \sigma_{a,b} \leq e_{a,b} \end{cases} \quad (2.8)$$

to be used together with Eq. (2.7)

In the second step of the DCF calculation we bin the UDCF values by time, such that

$$\text{DCF}(\tau) = \frac{1}{M} \text{UDCF}_{ij} \quad (2.9)$$

for each time interval $\tau - \frac{\Delta\tau}{2} \leq \Delta t_{ij} < \tau + \frac{\Delta\tau}{2}$. The normalisation factor, M , represents the number of UDCF points in the current bin, and accounts for the unequal number of UDCF values in each bin. The DCF is not defined for any τ corresponding to an empty bin, and it follows that the bin width must be chosen to minimise the tradeoff between DCF resolution and accuracy given by a high value of M . Given the definition of the DCF as the mean values of the sets of UDCF points, [Edelson & Krolik \(1988\)](#) define the associated uncertainty of the DCF by

$$\sigma_{\text{DCF}}(\tau) = \frac{1}{N'} \sqrt{\sum [\text{UDCF}_{ij} - \text{DCF}(\tau)]^2}. \quad (2.10)$$

The normalisation factor N' is commonly given by $\sqrt{M(M-1)}$, where the first M comes from the definition of the standard deviation of the mean, $\sigma_{\text{mean}} = \sigma/\sqrt{M}$, and $(M-1)$ comes from the definition of the corrected sample standard deviation. This expression for the normalisation factor N' assumes the measurements are independent, an incorrect assumption for correlation values between continuum and emission-line light-curves. Because the emission-line is achieved through smoothing of the continuum light-curve, correlation information will bleed into neighbouring measurements. We follow [Edelson & Krolik \(1988\)](#) in defining

$$N' = \sqrt{(M-1)(M'-1)}, \quad (2.11)$$

where M' is the number of different measurement times t_i for the data-points a_i in the bin. This is an approximate geometric mean between the total and the uncorrelated number of measurements

counting towards the sample standard deviation, and it provides a reasonable estimation when paired with Eq. (2.10).

2.3.2 Recovery of AGN Time-Lags with Associated Uncertainties

Similarly to other cross-correlation functions, the DCF peaks for the value corresponding to the phase shift yielding maximum similarity between the ingoing signals. The discrete nature of the DCF introduces a quantisation error, which becomes particularly prominent when bins are based on a low number of UDCF points, an effect caused by low sampling of light-curves. To avoid this digitisation noise, we fit the DCF, weighted by the DCF uncertainty, with a Chebyshev function of adaptive order, and accept the peak of the fitted Chebyshev function as the recovered time-lag value. To avoid the digitisation noise, it is important the Chebyshev function does not follow the DCF precisely, but is kept to a low enough order. As such, it is possible for the DCF to sometimes peak closer to the underlying lag than the fitted Chebyshev function, however, this is largely a random effect of the digitisation noise, and we have found the Chebyshev fit to provide an improvement in lag recovery for in most cases, particularly when considering a wide variety of light-curve qualities. An example of DCFs with Chebyshev fits used for lag recovery is shown in Fig. 2.11, where we have included an example of a lag recovery for a light-curve realisation whose DCF function peaks somewhat closer to the underlying lag than the associated Chebyshev function.

To fully contextualise the lag recovery, we additionally provide an estimation of the statistical and systematic uncertainties for the recovered lag. We estimate the “statistical” uncertainty by bootstrapping the UDCF values, repeating the lag recovery with different subsets of data going into the calculation of the DCF, and calculating the standard deviation of the recovered lags. To estimate an additional “systematic” uncertainty, we generate a large number of mock light-curve pairs based on the observable properties of the original light-curve pair, and calculate the standard deviation of the recovered lags obtained from each mock light-curve pair. We present an example of two light-curves with resulting DCF, lag recovery, and associated uncertainties in Fig. 2.11. The light-curve pairs are the same as in Figs. 2.9 and 2.10, where we have added “observational” uncertainties to the light-curves from Fig. 2.9.

2.3.3 Stacking with the Discrete Cross-Correlation Function

While Eqs. (2.7) to (2.11) most commonly are utilised for lag recovery of single AGN, they also provide a simple, yet effective method for lag recovery of a group of sources. While individual AGN observations are uncorrelated, their cross-correlation functions are expected to sample a common time-delay structure. Provided we pick AGN whose underlying, rest frame lags are similar, we expect the UDCF correlations to follow a similar pattern for time-lags around the common, representative lag of the AGN. Conversely, at time-lags far from the representative lag the correlations should be expected to be different, and average out to zero. By combining the UDCF values from different AGN to calculate a single DCF, a process we henceforth will refer to as stacking, we effectively

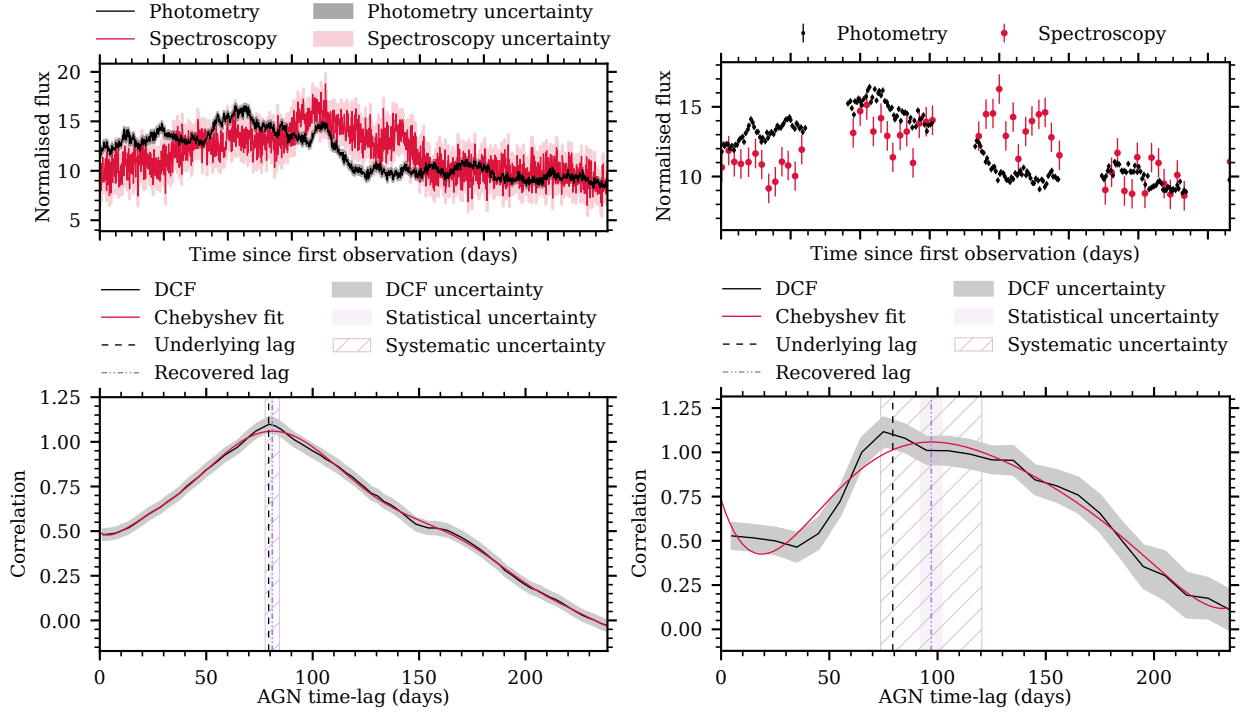


FIGURE 2.11: Effective continuum and emission-line light-curves based on the same underlying light-curve pair, shown in Fig. 2.9, are shown for a high sampling scenario (top left) and a low sampling scenario (top right). The resulting DCFs with associated uncertainty are shown below each effective light-curve pair. Additionally, we plot the Chebyshev fit to the DCF, used to determine the value of the recovered lag, which is shown with associated statistical and systematic uncertainty. The bottom right plot shows that digitisation noise at times allows the DCF to peak closer to the underlying lag than the Chebyshev fit, however, when assessing lag recovery for a range of light-curve qualities, the Chebyshev function generally allows for lag recovery with higher accuracy.

increase the numbers M and M' , and are as such provided with an improved estimate of the underlying parent function. The resulting improvement in accuracy and resolution of the DCF is equivalent to a higher sampling of a single AGN. Furthermore, using sources observed over a modest range of redshifts allows to expand the effective window-function by the span of cosmic time-dilations applied to the common survey window-function. AGN stacking thus allows to circumvent low sampling rates with the trade-off of a lower number of lag recoveries. The technique has been successfully demonstrated using MMT+PanSTARRS MDS (Multiple Mirror Telescope, Panoramic Survey Telescope & Rapid Response System medium deep survey) data (Fine *et al.* 2012, 2013).

The ability to trade a high sampling rate for a large number of targets is highly applicable for RM performed with multi-object spectroscopy instruments, including the OzDES RM program (see Sec. 1.3). To obtain a robust understanding of the stacking methodology, and how it compares to individual lag recovery, we test the outcomes of both methods rigorously, and compare them to each other in Sec. 3.1. We analyse different approaches to stacking, and their applicability to observational data in Sec. 3.1.2. Chap. 3 concludes with an application of the stacking methodology in an optimised manner to representative mock data in Sec. 3.2, and OzDES RM observations in

Sec. 3.3. In Chap. 4 we expand on the analysis, performing tests for light-curves with sampling representing a range of different survey strategies, and spanning a wide portion of the $r-L$ parameter space.

3

Reverberation Mapping in Bulk

The use of multi-object spectroscopy for RM programs – and what is consequently becoming known as RM in bulk, or industrial scale RM – opens up for the possibility of a statistical approach to RM analysis through stacking (Fine *et al.* 2012, see also Sec. 2.3.3). We wish to ensure not only that stacking is possible, but that the method also provides improved RM results over lag recovery of individual sources. We probe the methodology outlined in Sec. 2.3 on mock data representative of OzDES RM observations, generated by the process described in Sec. 2.2, to ensure the validity of our lag recovery procedure on individual sources and samples of AGN alike. Provided we can justify the use of stacking to improve OzDES RM results, we additionally require knowledge regarding how AGN samples should be chosen to maximise scientific results before being able to apply the methodology to observational data itself.

3.1 Predictions from Simulations

Simulations represent an important aspect of RM, because they allow testing the lag recovery method of choice. While a lag recovery method may provide a lag recovery of observational data, knowing whether the lag recovery method outputs the true value of the lag between two light-curves is of grave importance. Additionally, simulations allow to test for breaking points. For our purposes, the progressive change of parameters dictating the window-functions sampling our mock data allow us to test which parameters are of most significant importance to the lag recovery, which can enlighten the results from observational data, and inform the planning of future RM surveys.

We focus in this thesis on AGN observed through the C IV emission-line (see discussion in

Sec. 2.1.3). The distribution of the OzDES RM targets fitting this description is shown with red points in Fig. 3.1, in redshift-luminosity parameter space. The AGN are spread over more than two orders of magnitude of spectral luminosity, however, the distribution is clearly most dense for $10^{45} \text{ erg s}^{-1} \lesssim \lambda L_{\lambda}(1350 \text{ \AA}) \lesssim 10^{46} \text{ erg s}^{-1}$, and for $z \lesssim 2.5$. While the lag recovery success will depend on a number of different variables, our initial expectation is for stacking to be most effective in the most populated area. The combination of similarity in underlying AGN parameters – their rest frame time-lag, specifically – and the high population density in these regions implies the most significant increase in signal-to-noise through application of statistical methods.

3.1.1 Lag Recovery For Individual Sources

We commence our analysis utilising mock data of individual sources to establish a baseline of results, utilising the method outlined in Sec. 2.2. We generate mock light-curve pairs for an AGN with properties representative of the densest part of the OzDES RM AGN distribution, indicated

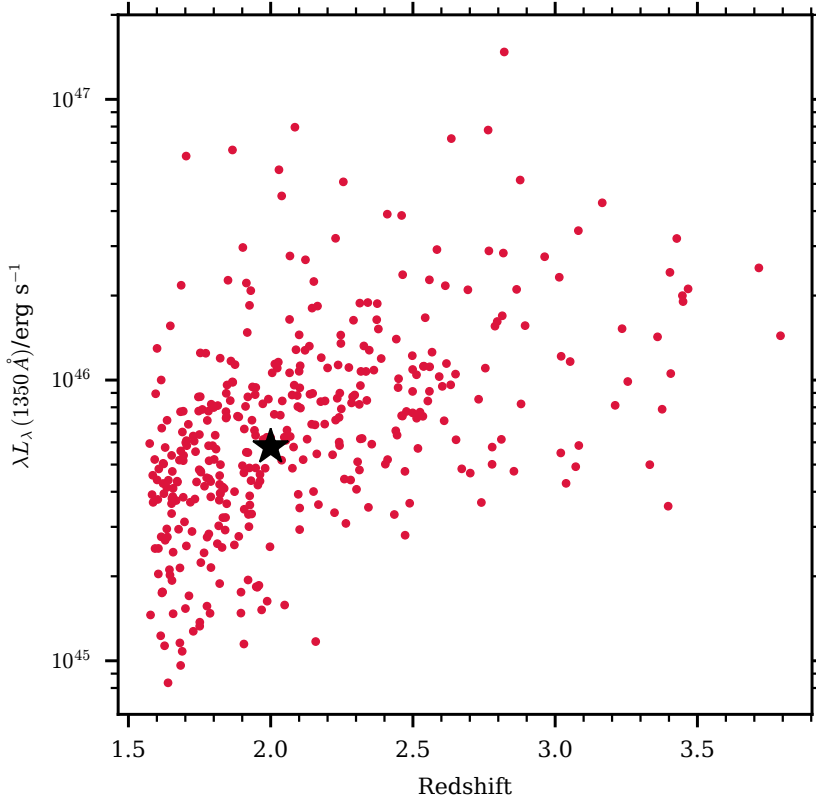


FIGURE 3.1: OzDES RM AGN whose C IV emission-line can be used for RM purposes (red points) in redshift-luminosity space, where the redshifts of the AGN are based on spectroscopic measurements, and the luminosities are the estimated spectral luminosities based on a combination of the observed redshift, apparent r -band magnitude, and assumed cosmology. In addition to the OzDES RM C IV AGN distribution, we illustrate the positioning of a theoretical AGN, representative of the densest part of the distribution (black star). We use the properties of this hypothetical AGN to create a series of mock light-curves to perform rigorous testing of lag estimation methods.

with a black star in Fig. 3.1. Choosing a representative AGN with these properties allows us to test individual lag recovery against stacked lag recovery in an area of parameter space where we expect stacking to be efficient, and thus make a significant change. To contextualise OzDES RM with other survey strategies (*e.g.* Peterson *et al.* 2005; Grier *et al.* 2012; Kaspi *et al.* 2007; Lira *et al.* 2018), as well as investigating the impact of the window-function on lag recovery, we probe the underlying mock light-curves with different window-functions, representing a variety of mock survey realisations. The mock survey strategies are generated to range from daily cadence to a combination of cadence and seasonal gap duration representative of the OzDES RM program. For consistency, the noise added to the underlying light-curves is kept at a level representative of OzDES RM for all window-functions. A sample of the results of the individual lag recovery analysis is shown in Fig. 3.2. The difference between the recovered and underlying lags is shown together with statistical and systematic uncertainty, calculated through the process outlined in Sec. 2.3.2, for three independent mock light-curve pairs probed with progressively sparse window-functions.

We note that deviation between recovered and underlying lag is small for highly sampled window-functions, however, as the window-function sampling decreases, the value of the recovered lag becomes increasingly unpredictable, with larger deviations from the underlying value. In terms of uncertainty, we find the systematic uncertainty increases steadily with lower window-function sampling, whereas the statistical uncertainty varies greatly in size. Further investigation of individual DCFs shows our chosen lag recovery method does not always reproduce the underlying lag value, a phenomenon whose frequency increases with lower window-function sampling. This inability to recover the correct time-lag value explains the lag recovery values' unpredictable deviation from underlying lag value, and – given our choice of statistical uncertainty estimation – the irregularity of the size of the statistical uncertainty.

The time-lag estimates in Fig. 3.2 illustrate that while our methodology sometimes recovers the correct time-lag values even when the light-curves have been sampled with a low density window-function, lag recovery is generally unreliable for window-functions with low sampling rates. To improve lag recovery, we performed an analysis of light-curve properties to establish a light-curve filtering process which would exclude light-curve whose lags were unlikely to be recovered. The following methods were tested, alone and in combination:

- *Variance requirements*

In simple terms, lag recovery with the DCF is based on finding the time-lag corresponding to the amount the light-curves must be shifted relative each other to be most similar. We expect our ability to find this amount to improve if the light-curve pair exhibits obvious trends which can be used for the matching process. By requiring the variance of the light-curves to pass a certain threshold, our efforts should in theory be focussed on light-curves whose trends are significant enough to yield lag recovery.

- *De-trending*

In some AGN light-curves, long-term variability will sometimes dominate the trends of a

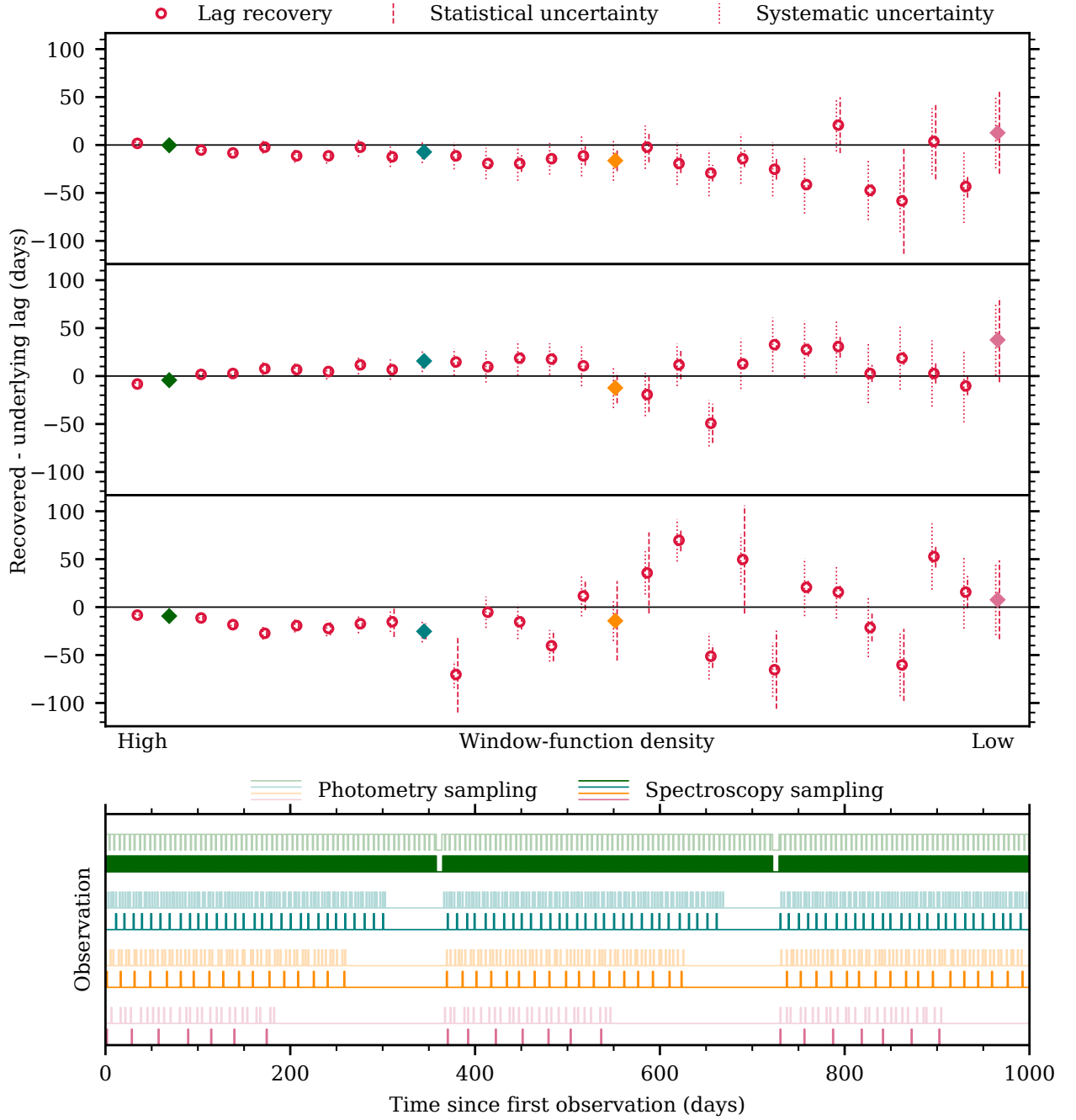


FIGURE 3.2: Effect of survey window-function on time-lag estimation is shown. The top three panels show difference between lag recovery and underlying lag value, with associated statistical and systematic uncertainties, for three independent mock light-curve realisations. From left to right an increasingly sparse window-function is used to down-sample each light-curve, photometric and spectroscopic. The window-function density transitions from daily cadence on the left-hand side of the panels, to observations representative of OzDES RM on the right. Four fiducial survey cadences are highlighted with green, turquoise, orange, and pink diamonds, and window-functions illustrative of their sampling are shown in the bottom panel using the same colour. For simplicity, only the first 1000 days of the full six-year window-functions are shown.

light-curve pair. In these cases, the challenge of lag recovery increases. These cases are also not caught by the variance requirement, as the variance will be based on the overall change of the light-curve, rather than the short-term variation itself. The method of subtracting a low-order polynomial from the light-curve, known as de-trending, has previously shown to help overcome these problems and improve lag recovery (e.g. [Welsh 1999](#); [Denney *et al.* 2010](#); [Peterson *et al.* 2014](#)).

- *Autocorrelation subtraction*

Individual inspection of DCFs revealed that a significant fraction of DCFs peak at lags considerably shorter than the underlying lag value, followed by a decrease in the correlation value. Based on this observation together with the fact that AGN light-curves are modelled by an autoregressive process, we investigated the possibility that a subtraction of the autocorrelation function of the photometric light-curve, or a variation thereof, from the DCF might eliminate the problem of premature peaks in the DCF.

No methodology allowed identification for a clean metric of light-curve appearance, leaving the standard lag recovery methodology as the most successful vehicle for lag estimation.

3.1.2 Lag Recoveries For Stacked Data

We follow the analysis of individual lag recovery with an examination of the stacked lag recovery method outlined in Sec. 2.3.3, and its potential to achieve more reliable RM results. To test the stacking approach we compute the stacked DCF for a sample of 20 mock light-curve pairs, sampled with a window-function representative of OzDES RM, and drawn from a parent sample with identical underlying parameters. We perform stacking, achieving a single DCF, with a single time-lag. To ensure the recovered lag is seen in a context, and does not represent a statistical outlier, we obtain a distribution of time-lag recoveries by repeating the stacking process 250 times, using different realisations of mock light-curve pairs each time. The distribution of stacked recoveries is shown as a red line in Fig. 3.3.

The real importance of stacking lies in the improvement it provides over lag recovery for individual sources. In addition to stacked lag recovery, we therefore perform lag recovery for individual mock light-curve pairs drawn from the same parent distribution as those used for stacked analysis. In addition to utilising a window-function representative of OzDES RM, we also sample the underlying mock light-curves with two window-functions of higher density. For each type of window-function we repeat the lag recovery process 250 times, to obtain comparative distributions, and show the outcome as a black line in Fig. 3.3. It is clear that the distribution of lag recoveries for mock AGN with a window-function representative of OzDES RM is significantly improved by the stacking procedure. Indeed, the distribution of lag recoveries for a stacked DCF resembles that of a single AGN probed with a significantly more dense window-function.

The example in Fig. 3.3, while illustrative of the power of stacking, requires modification to better represent realistic observational data. We modify our method to account for the diversity

of real AGN by allowing for stacking of sources which are different, but expected to have similar time-lags, knowing well that there must be a trade-off between stacking together AGN similar enough to represent a small range of lags, and the number of AGN observed whose lags fall within that range. We additionally find it necessary to modify the estimation of systematic uncertainty, since repetition of the procedure with alternative light-curve realisations is not possible with observational data. Instead, we use random sampling without replacement of the sources in the sample, each time picking 80% of the sources. We recover the time-lag for each random sample, repeating the process 250 times, or the maximum number of different combinations if below 250, and accept the standard deviation of the recovered time-lags as the systematic uncertainty of our lag recovery.

There are two effects whose impact on lag recovery we need to understand when moving to more realistic data. First, the effect of performing stacking for AGN whose underlying lags are intrinsically different. Second, the estimation of systematic uncertainty by reusing data through random sampling without replacement, according to the procedure outlined in the previous paragraph. We

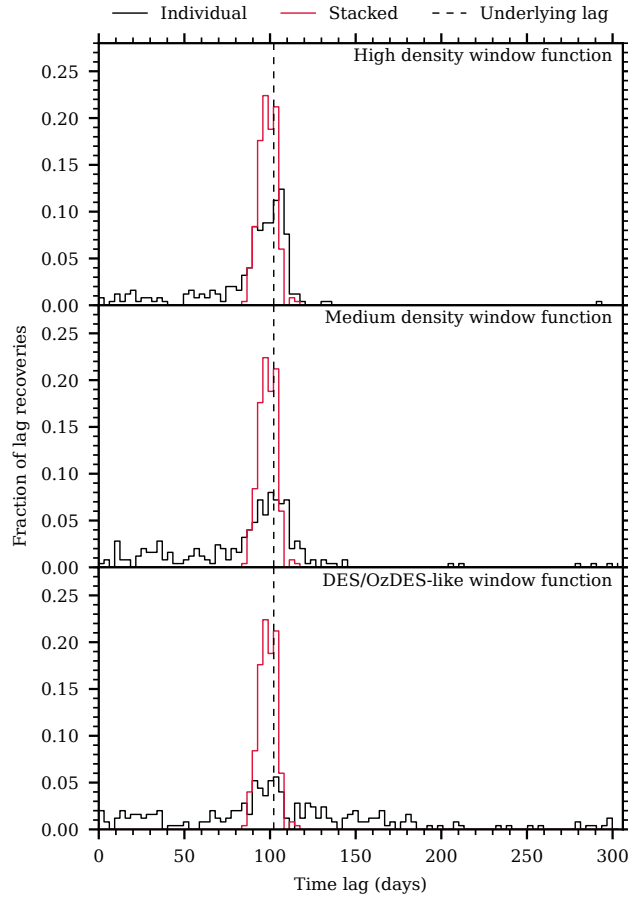


FIGURE 3.3: We compare the effect of stacking 20 mock AGN (with identical underlying properties) sampled with a window-function representative of OzDES RM to lag recovery of individual sources drawn from the same parent sample. Stacking significantly improves the accuracy and precision of lag recovery. Indeed, the distribution of stacked lag recoveries for sparsely sampled light-curves resembles the distributions of individual lag recoveries using light-curves sampled with a high density window-function.

create four sets of mock AGN to study each effect individually. Each sample contains 50 mock AGN, where two of the samples contain data with identical underlying parameters, and the two remaining samples contain AGN whose lag distribution has a standard deviation of 5% of the average lag value. By repeating each experiment five times we ensure our results are not biased by any single realisation, which is particularly important when testing the effect of reusing the same light-curves through random resampling. In Fig. 3.4 we compare stacking of AGN with identical parameters to stacking of AGN whose parameters are different, and the use of different mock light-curve realisations compared to random sampling without replacement of a single set of light-curves. We find the following: Using AGN which are intrinsically different from one another has not induced any significant loss of accuracy for the lag recoveries when compared to stacking AGN with intrinsically identical properties. We do, however, find a difference in lag recovery when light-curve pairs have to be reused, compared to if we could redo the stacking using different light-curve realisations. Using different AGN realisations ensures the lag recovery distributions are relatively self-consistent between experiments. When we reuse light-curves through random sampling, however, the limited information available seems to bias the results due to the presence of specific structure in each

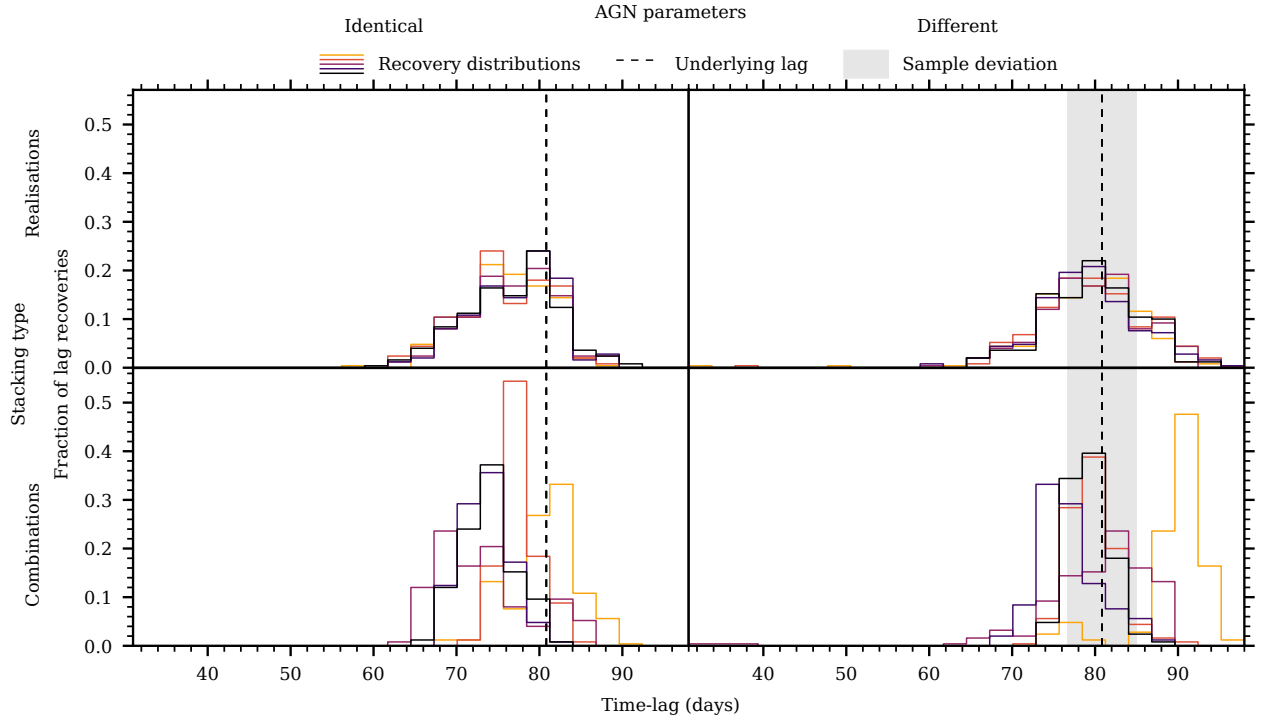


FIGURE 3.4: Comparison of effects on lag recovery caused by underlying AGN parameter values and stacking methods. The distributions on the left show the recovered time-lags for mock AGN which were created using identical underlying parameter values. On the right the mock data was created using a range of underlying parameter values, causing a range of time-lags, whose standard deviation is indicated by the grey field. The top plots show the distribution of recovered lags using a range of different mock light-curve realisations, where each realisation was used once to achieve a single lag recovery. In contrast, the bottom plots show distributions of recovered lags where each recovery corresponds to a different combination of a subset of light-curve pairs.

light-curve. Since the DRW, used to model our light-curves, is a stochastic process with a relaxation time-scale comparable to our observational window, individual light-curves can present weak or strong variability signatures in any given realisation. In contrast, using different light-curve pair realisations allows us to explore the lag parameter in a representative manner. When dealing with observational data one should therefore show additional care in interpretation of lag distributions, and the systematic uncertainties derived therefrom.

To quantify the effectiveness of the stacking methodology for observed data over that of individual lag recovery we create a parent sample of AGN with an underlying lag distribution with a standard deviation of 10% of the average of the lag values. We recover lags for 10 individual mock AGN, and perform stacked lag recovery for 2, 5, 10, 25, 50, 100, and 200 AGN at a time, repeating each stacking experiment 10 times. In Fig. 3.5 we show the ten lag recovery results for each number of AGN. The results are presented as the deviation of the recovered lags from the (average) underlying lags used for the mock light-curves, as well as the statistical uncertainties associated with each lag recovery. By fitting a power law to the lag deviations, we find that the error in lag recovery decreases as $n^{-0.22}$ for n AGN stacked together. Examining the statistical uncertainty, we find that lag recovery using a small number of sources creates a broad distribution of uncertainty values, accompanied by significant outliers. These outliers have a significant influence on the out-

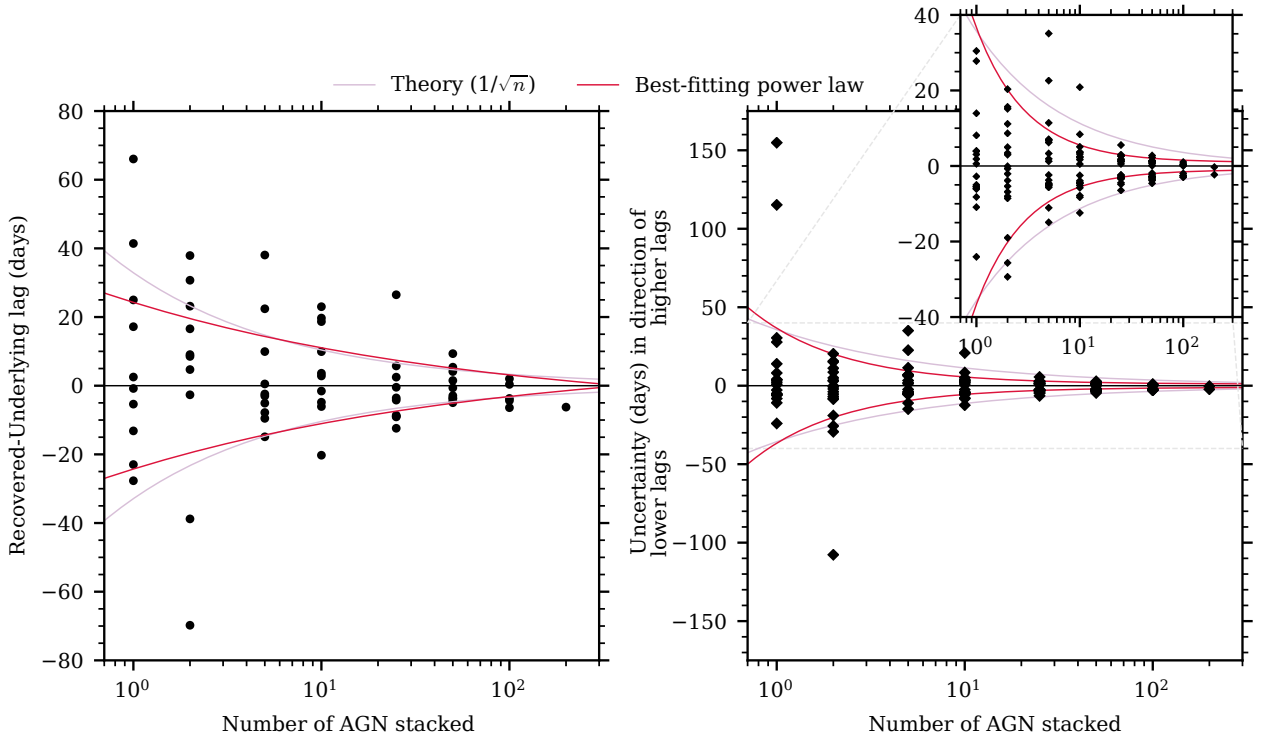


FIGURE 3.5: Deviation between lag recovery and underlying average lag of stacked AGN (left), as well as associated statistical uncertainty for the lag recovery when stacking different numbers of AGN (right, with a zoomed in view shown in the top right corner). Additionally we show the best fit power law for decrease in lag estimation error together with the theoretical prediction.

come of the fitting algorithm. To avoid bias caused by small number statistics, we choose to instead perform the fit using stacking of a higher number of AGN. Assuming we need >10 AGN to compute the trend of decrease with number of AGN, we find the statistical uncertainty to decrease as $n^{-0.25}$. These trends have both been plotted together with the theoretical uncertainty reduction of $n^{-0.5}$ in Fig. 3.5.

3.2 Stacking of Mock Data

To perform an OzDES RM specific stacking analysis we define a series of redshift-luminosity bins to cover the parameter space spanned by the AGN, specifically those observed through the C IV emission-line, according to the arguments presented in Sec. 2.2. The bins should ideally be kept narrow along the luminosity axis to ensure the sources within the bin have similar underlying rest frame lags. The use of bins along the redshift axis is not strictly necessary, since the use of AGN with a wide range of redshifts allows for the effects of cosmological time-dilation to fill in some temporal coverage gaps in the window-function caused by adverse weather events and the seasonal survey gaps. The bins must also be large enough to include a sufficient number of AGN to make a stacking analysis worthwhile.

We define our bins using the location of OzDES RM C IV AGN in redshift-luminosity space as a starting point, adjusting the bin edges in luminosity such that the standard deviation of the expected lags for sources within the bin is $\leq 10\%$ of the mean expected lag value for the bin. Given the relatively high number of AGN, we choose to break the sample up into three redshift bins. A small number of redshift bins allows to keep the number of AGN high in each bin, whilst simultaneously allowing to test for potential evolutionary effects within the $r - L$ relationship, provided the results are of high enough quality. Using these criteria, but allowing for minor adjustments to include as many sources as possible, we find that the majority of the OzDES RM C IV AGN can be covered using 13 bins. The bins are shown in Fig. 3.6 together with the distribution of our targets, with details regarding the bins in Tab. 3.1. It should be noted that the specific locations of the bins and their edges are not of crucial importance to the analysis, but were chosen to fit and summarise the distribution of the OzDES RM C IV AGN. While these bins are particularly suitable for OzDES RM data, they could be used by any RM survey observing AGN in the same region of parameter space, provided the number of AGN in any bin is high enough. However, in the circumstance that the bins are used by a different RM survey, the results outlined in the following sections are likely to change if the survey strategy of the alternative survey differs from that of OzDES RM.

3.2.1 Investigation of Parameter Space

While we defined all our bins to span the same range of lags per-cent-wise, we expect the success of lag recovery to vary across bins. The number of AGN present in each bin will certainly contribute towards lag recovery success, however, our ability to correctly recover lags representative of the sources within may also be dependent on the bins position in parameter space. We investigate

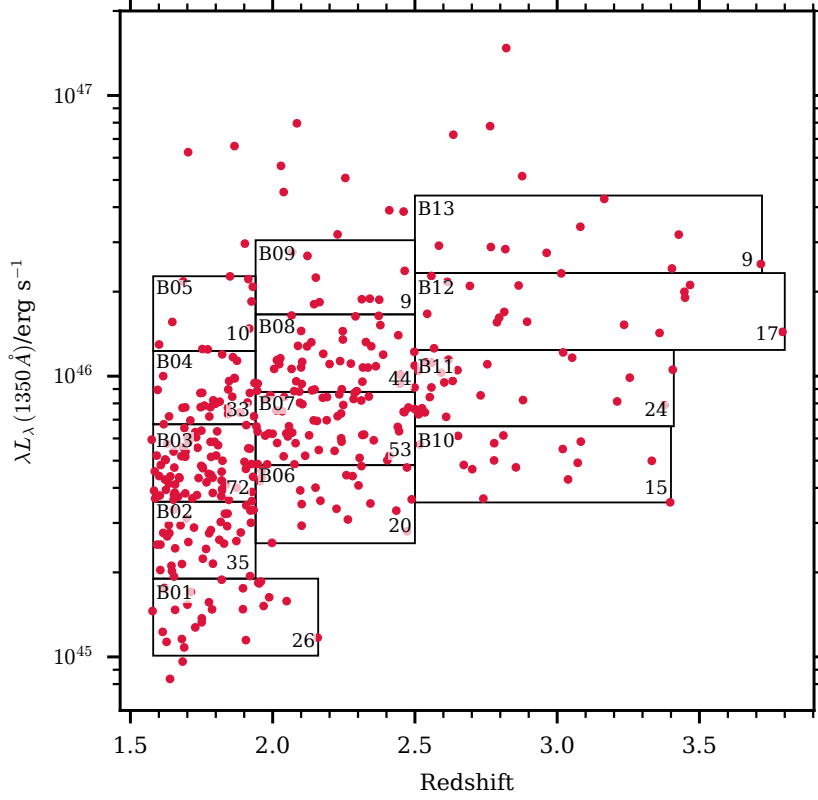


FIGURE 3.6: The same distribution of OzDES RM AGN as in Fig. 3.1, but with chosen binning of the AGN overplotted (black edged rectangles). The name of the bin is shown in every top left corner, and the number of AGN in the bin is in the bottom right.

each bin individually by creating mock light-curves and stacking them together. To ensure our simulations are as realistic as possible, we base the light-curves on the AGN parameters of the OzDES RM sources in the bin, and use the photometry and spectroscopy observing dates as our window-functions. We investigate the resulting lag recovery to make a judgement on whether the

TABLE 3.1: Binning of OzDES RM C IV AGN.

Bin name	$z_{\min}$	$z_{\max}$	$L_{\min}$	$L_{\max}$	AGN number
B1	1.58	2.16	1.01	1.90	26
B2	1.58	1.94	1.90	3.57	35
B3	1.58	1.94	3.57	6.74	72
B4	1.58	1.94	6.74	12.3	33
B5	1.58	1.94	12.3	22.7	10
B6	1.94	2.50	2.54	4.82	20
B7	1.94	2.50	4.82	8.79	53
B8	1.94	2.50	8.79	16.6	44
B9	1.94	2.50	16.6	30.5	9
B10	2.50	3.40	3.55	6.63	15
B11	2.50	3.41	6.63	12.4	24
B12	2.50	3.80	12.4	23.3	17
B13	2.50	3.72	23.3	44.0	9

Note. The luminosity is the spectral luminosity $\lambda L_{\lambda}(1350 \text{ \AA})$, where the values are given in units of $10^{45} \text{ erg s}^{-1}$. The AGN number represents the number of AGN within each bin. Blue rows indicate bins where the expected stacked lag recovery coincides with a seasonal gap.

bin should be deemed trustworthy when using observational data. To ensure the result is not biased by the specific light-curve realisation, we repeat the experiment 10 times for each bin before making a final judgement. In Fig. 3.7 we show DCF examples for two bins – in one we expect to achieve a reliable stacking result, in the other the results should be interpreted with great caution. We further show an example of how the DCF for the same bin may look different between two light-curve realisations, yet still suggest the results of the bin should be trusted in both cases in Fig. 3.8.

We compare the recovered value of the lag for each bin to the average value of the rest frame lags of the AGN in the bin. In Fig. 3.9 we summarise the study of lag recovery success for the different bins by colour coding the bins according to the tendencies to recover the average lag of the AGN present. As expected, the bins perform differently, however, we find that the bins with poor performance coincide with specific properties. We discuss these bins and their properties in Sec. 3.2.2.

3.2.2 Parameter Space Influence on Lag Recovery

According to our findings in Sec. 3.1.2, we expect stacking to be more effective with increased number of sources. It is therefore not a surprise that the least populated bin, B13, is not expected to be a highly reliable bin for stacked lag recovery. Bins B05 and B09 suffer from similar problems, and while bin B05 falls in the middle category in terms of reliability for correct lag recovery, it is likely the discrepancies between lag recovery and average underlying lags for this bin are caused by the low number of sources stacked together.

King *et al.* (2015) used mock data representative of the expected outcome of OzDES RM to predict the program’s lag recovery rate. They showed lag recovery would be more successful for AGN whose lags are close to a year in the observed frame, whereas lags close to $365 \cdot n_{\text{odd}}/2$ days, for odd integer values n_{odd} , would present a challenge due to the half-yearly seasonal gaps of OzDES RM. Among the five bins we deemed to be unlikely to provide successful lag recoveries (see Fig. 3.9), three of them correspond to bins where the average lag takes a value close to $365 \cdot n_{\text{odd}}/2$ days in the observed frame. While the average lag of bin B02 in observed frame is further away from $365 \cdot n_{\text{odd}}/2$ days than the average lag of bin B03, both bins could be negatively influenced by the seasonal gaps of our window-function. Bin B02 has an additional disadvantage in being a bin spanning a low range of redshifts. A narrow distribution of redshifts is disadvantageous due to the implication that the effect of time-dilation filling gaps in the observational window-function will be small, thus making stacking less effective.

Taking into consideration the properties of the parameter space, and the OzDES RM population thereof, the analysis summarised in Fig. 3.9 represents a reasonable approach to the coming interpretation of observational results. It should be noted that while only four bins were classified as highly likely to provide a reliable lag recovery, the stacked lag recovery of observational data may be successful for any bin. Fig. 3.9 should serve as an indication of the carefulness with which a lag recovery should be interpreted as correct.

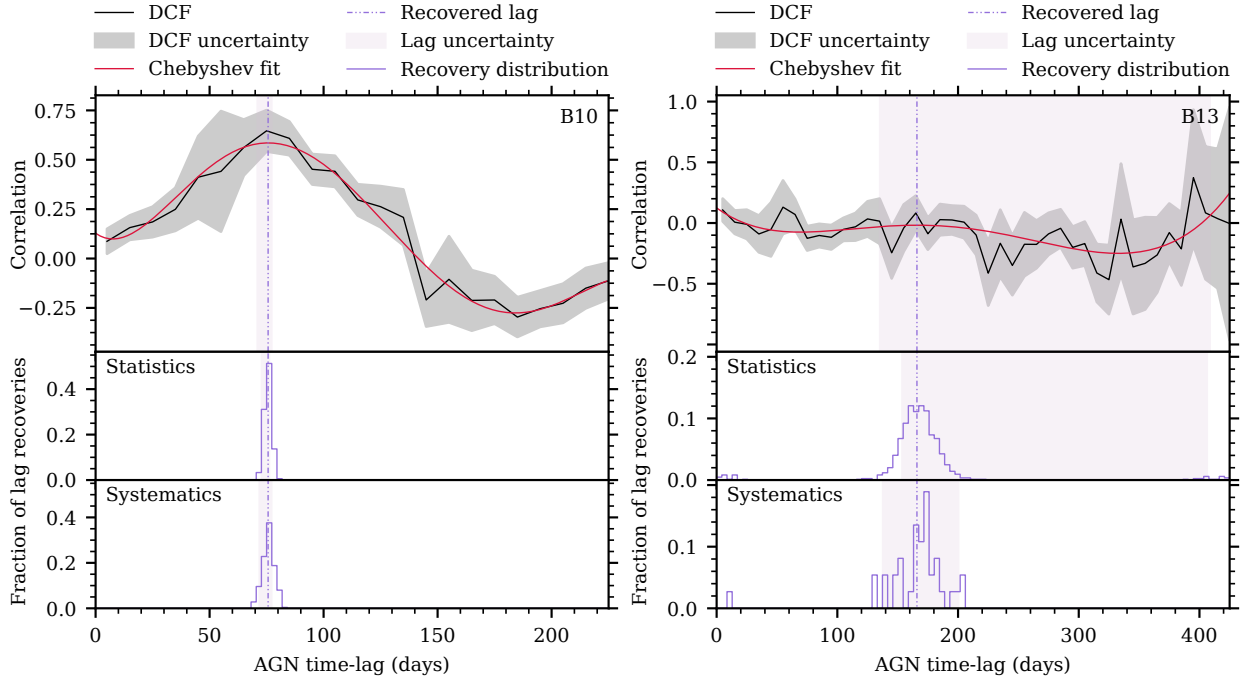


FIGURE 3.7: DCFs for one of the light-curve realisations for bins B10 (left) and B13 (right), whose details are described in Tab. 3.1. For B10 the Chebyshev fit provides a good fit for the DCF, which has a clear peak. The statistical and systematic uncertainties have narrow distributions centred on the recovered lag value. Bin B10 exemplifies a trustworthy stacking result, and a bin we expect to get successful lag recovery for when using observational data. Conversely, the DCF for B13 is dominated by noise, and the high statistical uncertainty in direction of higher lag values indicates the DCF peak is found to exist at two distant locations for a non-insignificant portion of the bootstrapping iterations, which is also reflected in the statistical lag recovery distribution. Based on this outcome, we flag B13 as a bin unlikely to recover reliable time lags for observational data.

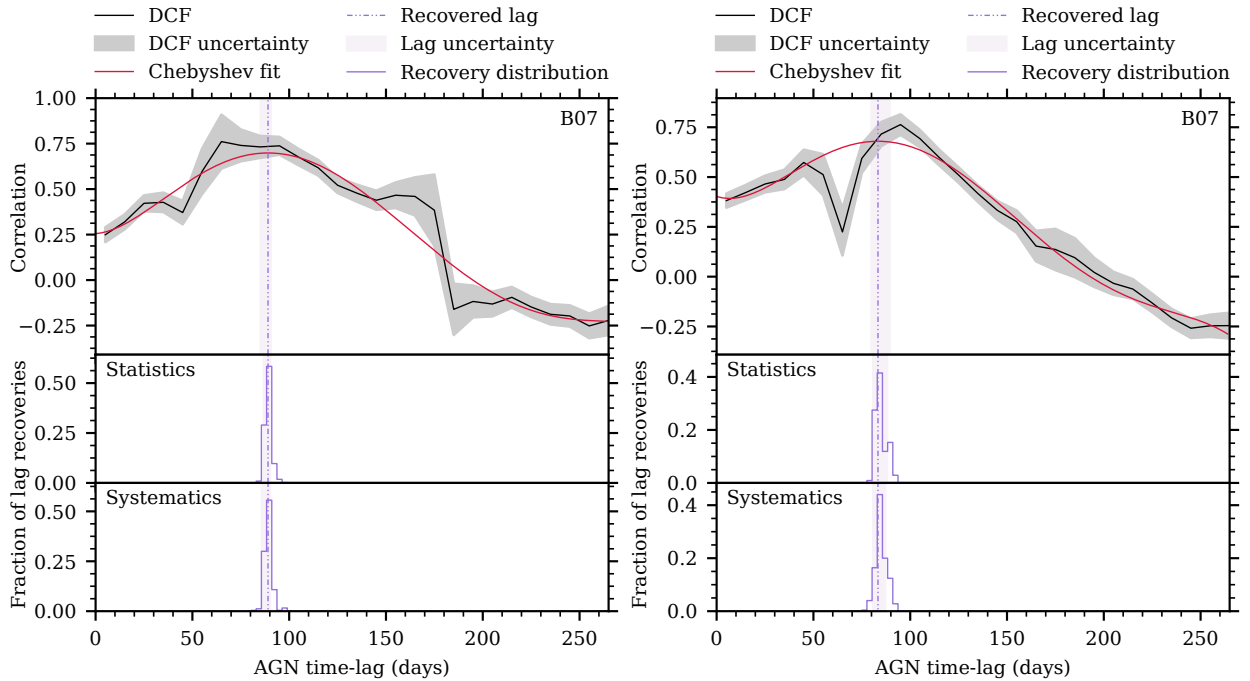


FIGURE 3.8: DCFs for two light-curve realisations for the same bin, B07, described in Tab. 3.1. The DCFs have a clear peak around a similar value in both instances, and the Chebyshev function fits the general shape of the DCFs well. A bin with these results can be expected to provide a reliable lag recovery for observational data.

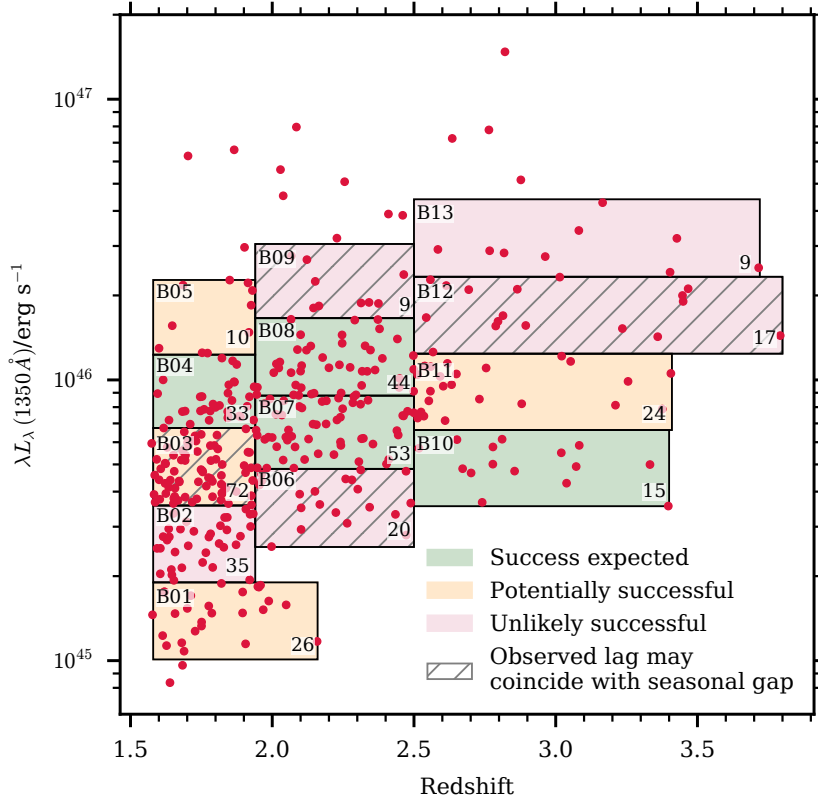


FIGURE 3.9: The same distribution of OzDES RM AGN as in Fig. 3.1, with the binning shown in Fig. 3.6 and detailed in Tab. 3.1 overlaid. The bins have their name and number of AGN shown in the top left and bottom right corners, respectively, and are colour coded based on the success of lag recovery for simulations, with the bins likely to be affected by seasonal gaps additionally highlighted. Successful lag recoveries with simulated data allow for additional trust when recovering lags for observational data. Conversely, a tendency of poor lag recovery for simulated data indicates caution should be shown in the interpretation of the results for observational data.

3.3 Stacking of Observational Data

With the knowledge of which bins are most likely to correctly recover lag values representative of the AGN within them, we apply the same lag recovery method to observational data. We attempt lag recovery for all bins, regardless of their classification based on simulated data. With a limited number of bins, we inspect each DCF individually to make an educated judgement on whether the lag recovery should be deemed successful or not. To assist with the decision making of lag recovery success, we consider also the results of nearby bins, since we expect similar lag recovery values for bins with AGN at similar luminosities. The lag recovery values of nearby bins can especially be important for bins such as B03, whose result may be influenced by the seasonal gaps in the observed frame, but should in the rest frame have a similar lag to B10, whose lag recovery is predicted to be successful.

We present the lags recovered through the stacked DCF method in Fig. 3.10 together with other C IV time-lags in literature (Peterson *et al.* 2005; Kaspi *et al.* 2007; Trevese *et al.* 2014; Lira *et al.*

2018; Grier *et al.* 2019; Hoormann *et al.* 2019), as well as the $r-L$ relationship used for simulations (Kaspi *et al.* 2007), and the two most recent $r-L$ reported in literature (Hoormann *et al.* 2019; Grier *et al.* 2019), one of them based on the first OzDES RM publication using C IV AGN. At first glance, the recovered lags may not seem to occupy an inappropriate section of parameter space. However, inspection of the stacked DCFs, which are shown together with their associated lag recovery and the histograms used for uncertainty calculations in Appendix A, reveals that the vast majority of the bins have DCFs which peak at values corresponding to lags differing significantly from our expectations based on the $r-L$ relationship of Kaspi *et al.* (2007). While a discrepancy between expected and recovered lags could be caused by an intrinsic scatter around the $r-L$ relationship, the lag recoveries do not appear to be as randomly distributed as one might expect in such a situation. Indeed, we generally find short lags to be estimated for AGN with long expected lags, and vice versa. It is not clear what selection criteria would cause a bias of our results to imitate a behaviour perpendicular to what is expected.

In addition to discrepancies between expected and recovered lag values, we further find that the stacked DCFs are noise dominated, with very low levels of correlation between the photometry and spectroscopy data. Based on the discrepancy between simulations and observed data, as well as the low quality of the stacked DCFs, we choose to continue our investigation without claiming the validity of the results portrayed in Fig. 3.10.

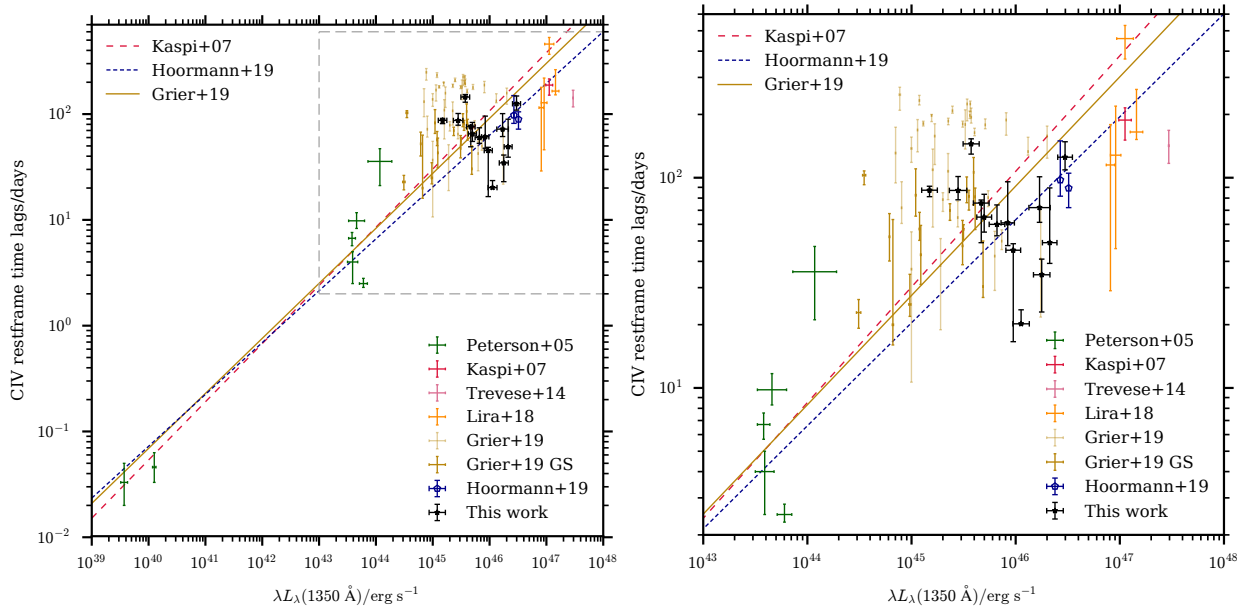


FIGURE 3.10: Lag-luminosity plot showing the lag estimation based on this work together with lags previously reported in literature. The $r-L$ relationships reported by Kaspi *et al.* (2007), Hoormann *et al.* (2019), and Grier *et al.* (2019) are shown for context. The recovered C IV lag values for all AGN reported thus far in literature are shown in the plot on the left. In the plot on the right, we exclude the AGN with the two shortest lags to better focus on the majority of results. The limits of the right-hand figure are indicated in the figure on the left using grey, dashed lines.

3.3.1 Investigating the Effect of Larger Bins

It is possible the observed OzDES RM data is of poorer quality than simulated, and a higher number of AGN is needed to successfully recover the time-lag signal. To stack higher numbers of AGN, we need to redefine the boundaries of the bins to allow more of them to be grouped at the same time. To expand the bin sizes along the luminosity would result in the stacking of AGN whose lags are intrinsically more diverse, an effect we are interested in limiting, particularly given the low presence of time-lag signal using the original bins. To expand the bins, we therefore eliminate the previous condition that the sample should be broken up into a number of redshift bins, and define our bins by luminosity restrictions only. We continue defining the widths of the bins by luminosity such that the standard deviation of the expected lags for the sources within the bin is $\leq 10\%$ of the mean expected lag value for the bin. The alternative set of bins is presented in Fig. 3.11, with details provided in Tab. 3.2.

The lags recovered using the alternative set of bins are shown in Fig. 3.12, using the same format as in Fig. 3.10 for easy comparison. The stacked DCFs together with associated lag recoveries are available in Appendix B. It is clear that the modification of the bins to increase the AGN number

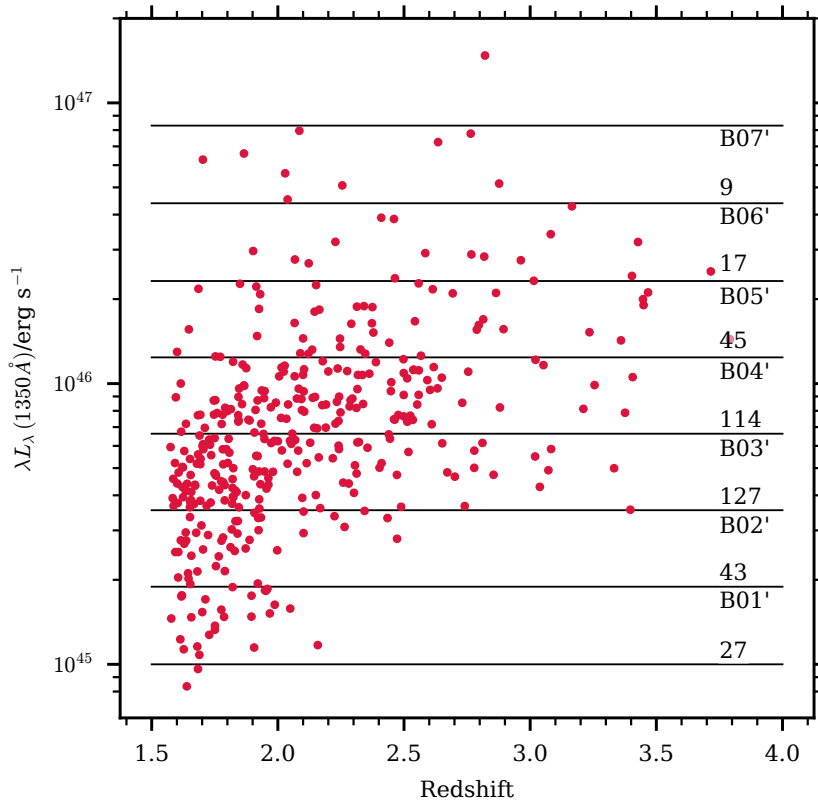


FIGURE 3.11: The same distribution of OzDES RM AGN as in Fig. 3.1, and derivations thereof, but with bins adjusted to span the full range of redshifts covered by the AGN observed by OzDES RM. The name of the bins is shown at the top right of every corner, with the number of AGN in the bin shown at the bottom right.

TABLE 3.2: Alternative binning of OzDES RM C IV AGN.

Bin name	$L_{\min}$	$L_{\max}$	AGN number
B1'	1.00	1.89	27
B2'	1.89	3.54	43
B3'	3.54	6.63	127
B4'	6.63	12.4	114
B5'	12.4	23.2	45
B6'	23.2	43.9	17
B7'	43.9	83.0	9

Note. The luminosity is the spectral luminosity $\lambda L_{\lambda}(1350 \text{ \AA})$, where the values are given in units of $10^{45} \text{ erg s}^{-1}$. The AGN number represents the number of AGN within each bin.

statistics did not improve the time-lag results. Indeed, lag recovery was not possible for B03', and the lag recoveries for bins B01' and B04' suffer significant uncertainties, caused by a lag recovery value which changes drastically depending on which subsets of data are used. It should be noted that while B01' largely contains the same AGN as B01, B03' and B04' are both bins whose AGN number has increased significantly by implementing wide bins. It is possible that noise caused by

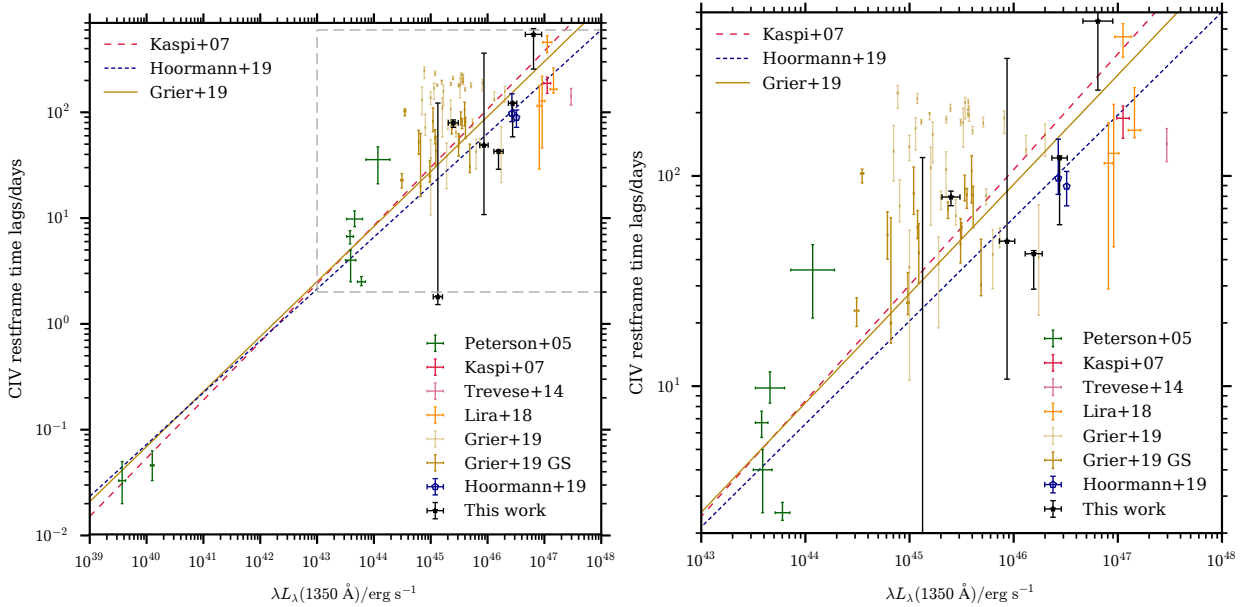


FIGURE 3.12: Lag-luminosity plot showing the lag estimates achieved using wider bins, together with lags previously reported in literature. The $r-L$ relationships reported by Kaspi *et al.* (2007), Hoormann *et al.* (2019), and Grier *et al.* (2019) are shown for context. The recovered C IV lag values for all AGN reported thus far in literature are shown in the plot on the left. We limit the plot using the same lag and luminosity limits as in Fig. 3.10 in the plot on the right, with limits of the right-hand figure are indicated in the figure on the left using grey, dashed lines. Using the same set of limits demonstrates the significance of disagreement of these results to those presented in Fig. 3.10, since the lag recoveries extend beyond the limits of the plot on the right.

poor quality data, particularly through inclusion of a high number of sources likely to be affected by seasonal gaps, has dominated the signal amplification that should have occurred from stacking a higher number of sources, thus leading to a poorer result than at the beginning of Sec. 3.3.

Stacked DCF lag recovery using the bins outlined in Figs. 3.6 and 3.11 and Tabs. 3.1 and 3.2 produced lag estimates which differ from expectations based on previous knowledge regarding the $r - L$ relationship for the C IV emission-line. Importantly, we found a significant discrepancy between the lag recoveries obtained using the same methodology with observational and simulated data. Since our simulations were based directly on known information regarding our AGN, this outcome discrepancy suggests the simulations were based on flawed assumptions, failing to consider one or more influential factors.

3.3.2 Assessing the Impact of Assumed $r - L$ Relation

Our chosen binning was in both cases based on AGN properties described by Eq. (1.4), the $r - L$ relationship found by [Kaspi *et al.* \(2007\)](#). The testing of parameter space performed in Sec. 3.2.1 was thus based on the assumption that the AGN follow properties which are in line with Eq. (1.4). To ensure the assumption regarding an underlying $r - L$ relationship does not bias or enshroud our results, we repeat the stacking analysis using the same bins as in the beginning of Sec. 3.3 (details are specified in Tab. 3.1), but modifying the properties of the light-curves through an alternative $r - L$ relationship. We choose the $r - L$ relationship reported by [Hoormann *et al.* \(2019\)](#),

$$\log_{10} \left[\frac{r_{\text{BLR}}}{10 \text{ light-days}} \right] = (0.82 \pm 0.08) + (0.49 \pm 0.02) \log_{10} \left[\frac{\lambda L_{\lambda}(1350 \text{ \AA})}{10^{44} \text{ erg s}^{-1}} \right], \quad (3.1)$$

and generate a new set of mock light-curves to evaluate stacked lag recovery for. Both $r - L$ relationships are shown together in Fig. 3.13.

We recover time-lags for the mock data based on the alternative $r - L$ relationship, and compare the DCFs to those obtained in Sec. 3.2.1. We find that the DCFs again show significant cross-correlation values, unlike those achieved for the observational data (see Sec. 3.3). While the new DCFs seem to be somewhat more dominated by noise than the previous simulations, resulting in poorer fits of the Chebyshev function, the fitting algorithm and lag recovery remain reasonable. An example of this, showing the DCF and time-lag recovery for the same bin, B11, is shown in Fig. 3.14 using data based on both $r - L$ relationships. We compare the lag recoveries based on the $r - L$ relationships described by Eqs. (1.4) and (3.1) to the relationship from which they are drawn, and show the result in Fig. 3.13, which illustrates that the lag recoveries follow the underlying relationship in both cases.

The results for simulated data, presented in Fig. 3.13, are shown together with the unreliable time-lags recovered for observational data. It is clear that if the AGN were better described by an $r - L$ relationship different from the one assumed, we might expect some complications with the lag recovery, however, the poor results obtained from observational data cannot be explained by an inconsistency due to assumptions about $r - L$ relationship alone. We are led to the unfortunate

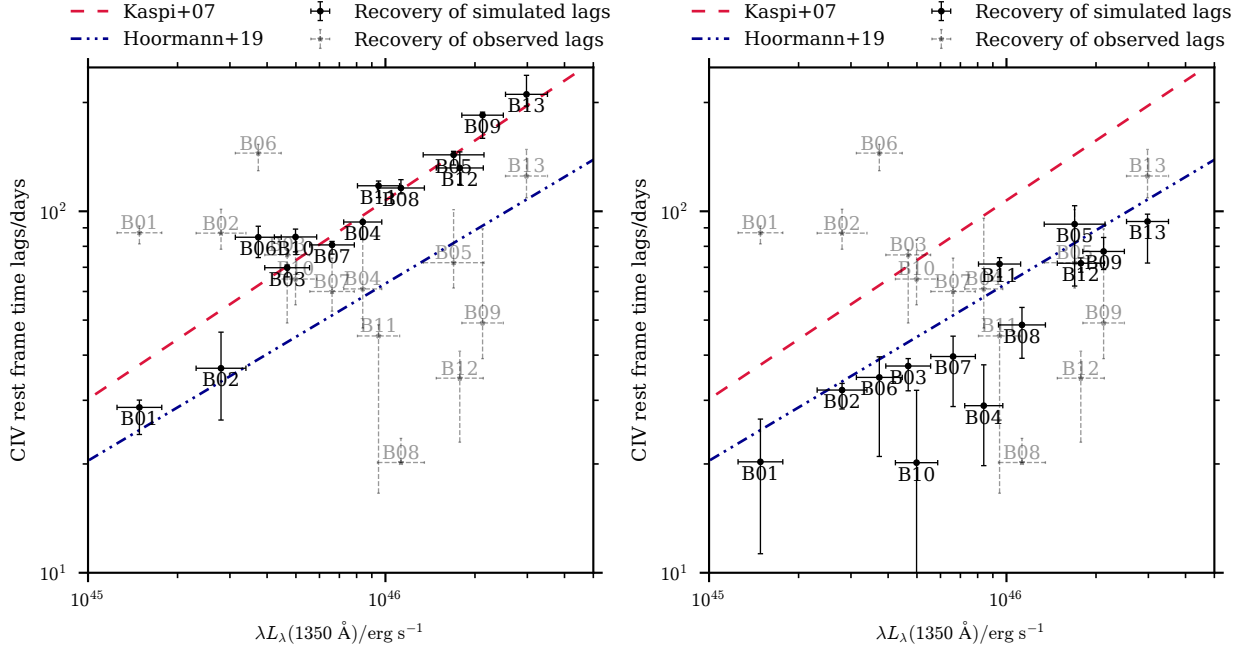


FIGURE 3.13: Two $r - L$ relationships are shown together with lag recoveries for simulated (black dots) and observed (grey stars) data. All data has been stacked using the bins represented by Figs. 3.6 and 3.9, and Tab. 3.1, based on the $r - L$ relationship of Kaspi *et al.* (2007, red, dashed line). The grey stars with dashed errorbars represent the lags we would obtain from the DCFs for stacking of observed OzDES RM light-curves, if we considered the lags to be recovered. The mock data was generated assuming the $r - L$ relationship of Kaspi *et al.* (2007, left), and Hoormann *et al.* (2019, right). While the lag recoveries based on the $r - L$ relationship reported by Hoormann *et al.* (2019) have larger deviations from the underlying relationship than those based on Kaspi *et al.* (2007), the effect is not large enough to explain the poor lag recoveries obtained for observational data.

conclusion that the stacking analysis, although showing great potential through simulations, has most likely not been successful for OzDES RM data. In Chap. 4 we investigate the potential reasons behind the null result of the stacking methodology, and discuss the implications for future RM surveys.

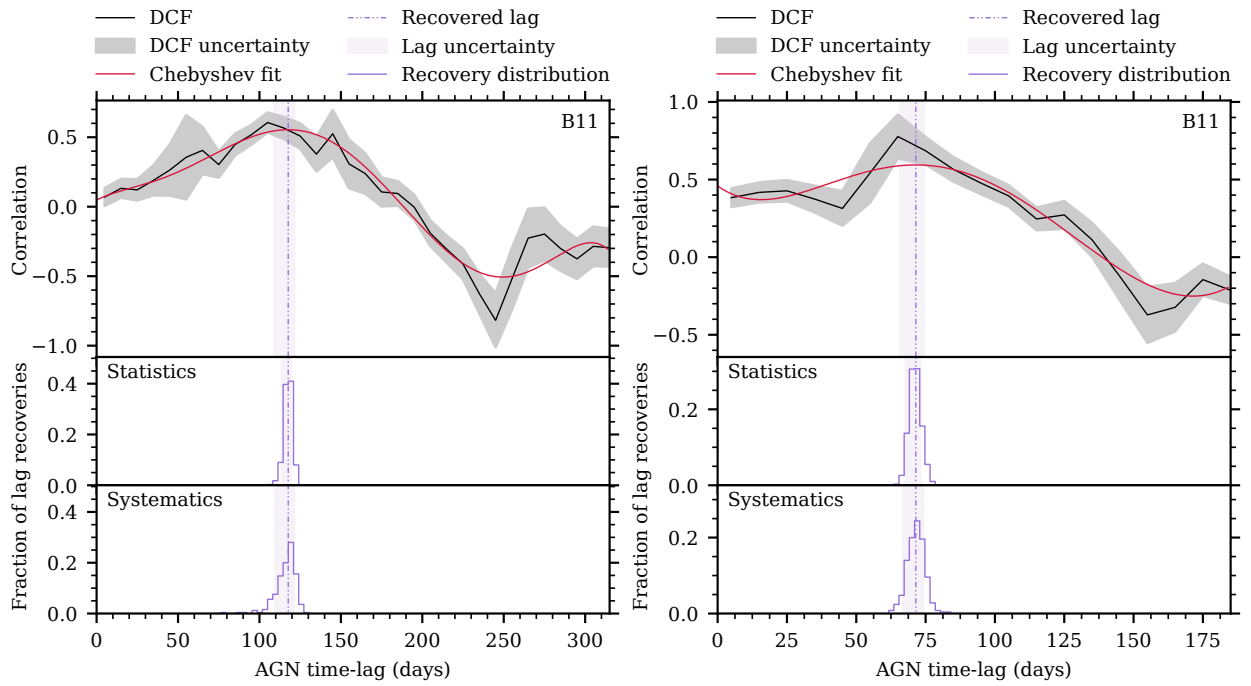


FIGURE 3.14: The DCFs for a single bin, B11, are shown when using the $r - L$ relationship reported by [Kaspi *et al.* \(2007\)](#), left), and that of [Hoormann *et al.* \(2019\)](#), right). The DCF peaks show similar levels of cross-correlation in both cases, with the Chebyshev function peaking at similar values. The DCF for the bin where the mock light-curves were generated using the relationship published by [Kaspi *et al.* \(2007\)](#) are slightly less impacted by noise than those generated using the relationship reported by [Hoormann *et al.* \(2019\)](#). This is likely caused by the fact that the bins were defined based on an assumption that the AGN follow the relationship of [Kaspi *et al.* \(2007\)](#).

4

Effect of Window Function

The analysis in Chap. 3 shows a discrepancy between the predictions based on simulations and the outcome using observational data. Simulations showed a statistical approach to RM through stacking should allow for lag recovery in cases where individual lag recovery failed, however, the application of the methodology to observational data did not prove to be successful. There are a number of possible reasons to why the same outcome was not achieved; the model for the transfer-function could be oversimplified, the assumption that the continuum light-curve can be modelled by a DRW could be incorrect, or the window-function may simply be posing a greater challenge than expected when combined with the intrinsic variations of the $r - L$ relationship. Exploring the nature of the continuum light-curve, and testing alternatives to the DRW is an extensive task, and beyond the scope of this thesis. We are thus left with the option of investigating the transfer-function, or the window-function.

The transfer-function, describing the way the BLR processes the continuum signal, is likely to be significantly more complicated than the top-hat function we utilise, which is widely accepted. More sophisticated lag recovery methods, such as **JAVELIN** (Just Another Vehicle for Estimating Lags In Nuclei, [Zu, Kochanek & Peterson 2011](#)), also assume a top-hat transfer-function, and was used by [Grier *et al.* \(2019\)](#) to achieve 52 recovered lags with SDSS-RM. Given the large number of successful lag recoveries by [Grier *et al.* \(2019\)](#) despite a similar set of light-curve assumptions, we focus here on the window-function and its impact on lag recovery. RM has been performed with a range of different survey strategies (e.g. [Peterson *et al.* 2005](#); [Grier *et al.* 2012](#); [Kaspi *et al.* 2007](#); [Lira *et al.* 2018](#)), and it is worth studying how the window-function may impact the recoverability of AGN lags.

4.1 The Impact of the Window-Function

We investigate the impact the window-function, describing the dates of observations, on our ability to correctly recover time-lags using the DCF approach described in Chap. 2. Lag recoveries are expected to be successful for a higher fraction of instances when the light-curves are highly sampled by the window-function. We follow the approach outlined in Sec. 2.2 to create three light-curve pair realisations for a single AGN in a dense area of the distribution of OzDES RM AGN observed through the C IV emission-line. In Fig. 4.1 we show the distribution of the AGN together with our mock AGN, denoted by a cross ($\times$). We probe the underlying light-curves of this AGN with progressively lower sampling, utilising nine window-functions based on survey strategies detailed in Tab. 4.1. For each AGN realisation, we combine each of the nine effective continuum light-curves with each of the nine effective emission-line light-curves, yielding 81 mock light-curve pair combinations for each

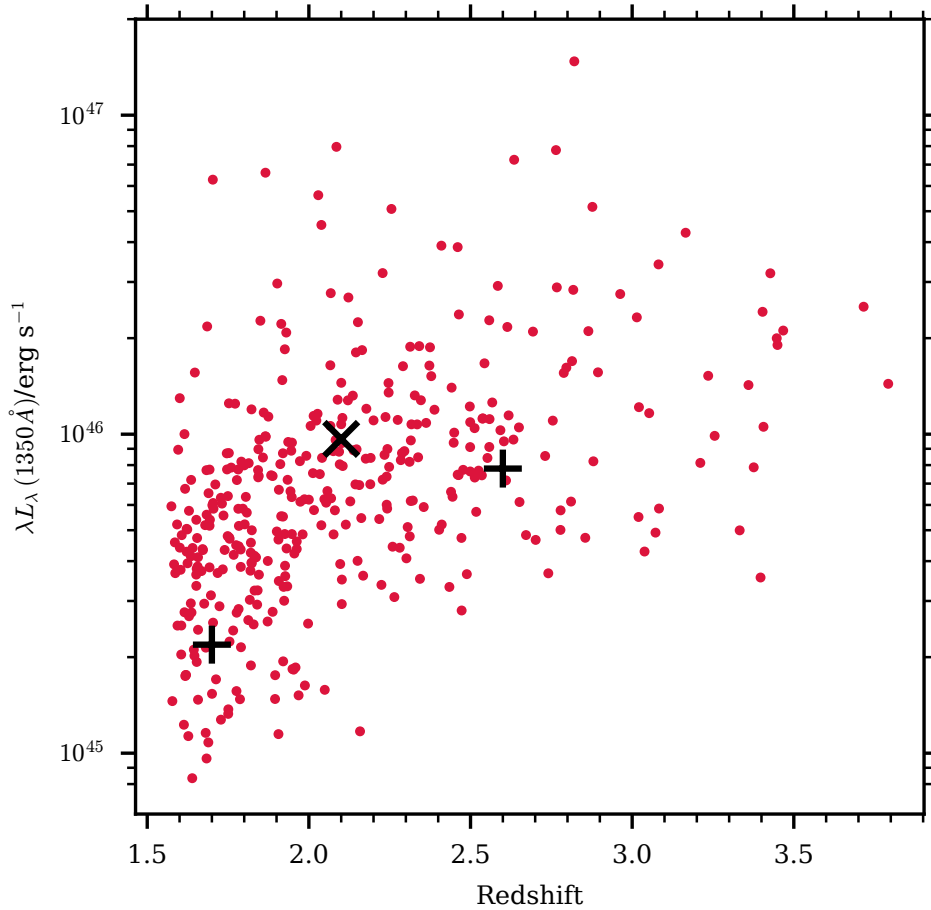


FIGURE 4.1: The distribution of OzDES RM AGN observed through the C IV emission-line (red dots) is shown together with three mock AGN used for testing the impact of the window-function on lag recoverability. We present multiple light-curve realisations for one AGN (black cross, $\times$) to ensure the lag recovery results are not caused by the specific light-curve realisation chosen. Additionally, we present a single light-curve realisation from two other AGN (black pluses, $+$) to demonstrate the results of the first mock AGN were not biased by the AGN's position in parameter space.

TABLE 4.1: The most important variables describing the window-functions used for Figs. 4.2 and 4.3.

Survey realisation	Average cadence (days)	Seasonal gaps [*] (days)
A	1	0
B	2	91
C	4	122
D [†]	7	153
E	14	182
F [‡]	28	182
G	56	182
H	84	245
I	365	351

^{*} The seasonal gaps represent the number of days per year where the regular cadence is omitted with no observations being undertaken.

[†] DES-like window-function

[‡] OzDES-like window-function

AGN realisation, and perform lag recovery for each of the window-function pairs. We note that a real RM program is unlikely to be designed with a sampling rate that is lower for the continuum than the BLR, but choose to include these pairs as a sanity check for the hypothesis that sparser sampling of light-curves will yield poorer lag recoveries.

The 81 lag recoveries for each of the three AGN realisations are shown in Fig. 4.2 together with their associated statistical and systematic uncertainties. We quote the lag as a difference between the recovered and the underlying lag, $\Delta\tau = \tau_{\text{recovered}} - \tau_{\text{underlying}}$, and the uncertainties as percentages of the recovered lag. The results are represented by a set of heatmaps, where each row of heatmaps represents a different realisation of the AGN, and each column a different aspect of the lag recovery. In each heatmap, the different tiles represent a different combination of effective light-curves, based on the window-functions for the continuum along the vertical axis, and the emission-line along the horizontal axis. The combination of window-functions representative of the OzDES RM survey strategy is marked by a hashed region overlaying the values representing the lag recovery. In addition to the regular colours of the heatmap, we include black and grey tiles. The black tiles correspond to light-curve combinations where the lag recovery failed entirely due to the shape of the resulting DCF. We use grey tiles to indicate lag recoveries where the resulting DCF did allow for a lag recovery, however, the value of one or more of the properties of the lag recovery is of concern. This can be due to a significant disparity between underlying and recovered lag, or the size of the uncertainty.

In accordance with the hypothesis that lag recovery is more successful for highly sampled light-curves and poorer for sparser window-functions, we observe the lag recovery to have the smallest uncertainties and deviations from the underlying lag value where the light-curves were highly sampled (upper left corner of each heatmap). Conversely, the unsuccessful lag recoveries are primarily found for sparse window-functions, and we observe the uncertainties increase in value for

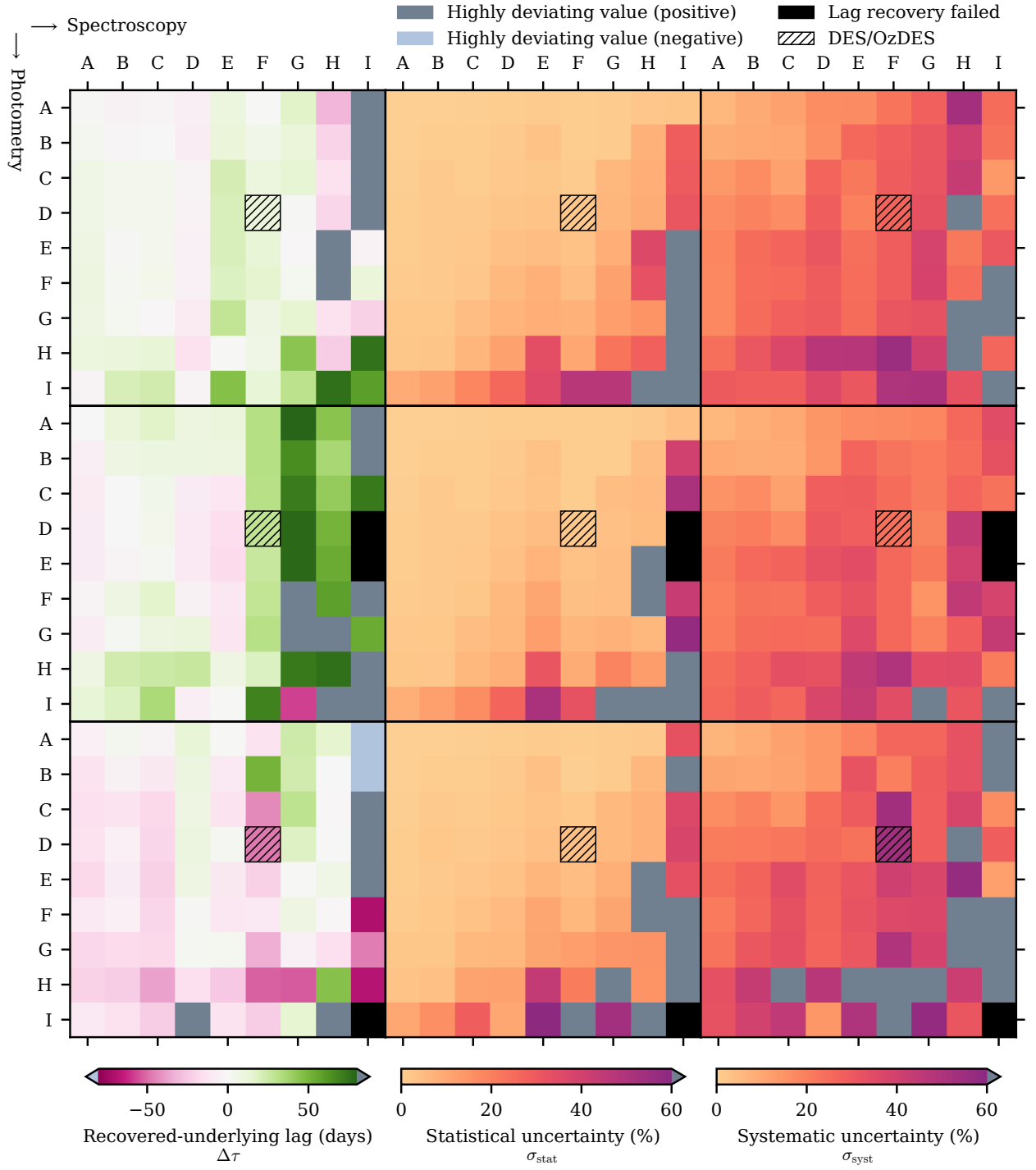


FIGURE 4.2: Individual lag recovery for three realisations of a single AGN, marked with a cross in Fig. 4.1, with the mock light-curves probed by a range of different window-functions A-I, detailed in Tab. 4.1. Each row of heatmaps represents one mock light-curve realisation for the AGN. The window-functions increase in density towards the top-left corner of each sub-plot. The lag recovery is shown in the leftmost column as the difference between recovered and underlying lag, specified in days. The statistical and systematic uncertainties, calculated following the process outlined in Sec. 2.3.2, are quoted as percentages of the recovered lag value in the middle and rightmost columns, respectively. Combinations of window-functions where lag recovery was not possible are marked by black, whereas grey is used for recoveries which were successful, but of significant disparity from underlying value (for first column) or with significantly large uncertainty (middle and right columns). The tile with the combination of window-functions representing the OzDES RM program is highlighted by a hashed region in each subplot.

the lower sampling of light-curves (bottom right corner of the heatmaps).

To ensure the results in Fig. 4.2 are not caused by the AGN being located in an unfortunate region of the OzDES RM parameter space, we generate two additional AGN to probe a wider range of parameter space. The additional AGN are shown in the redshift-luminosity parameter space together with the previous mock AGN in Fig. 4.1, and are denoted by plus-signs (+). We use the same approach as for the generation of Fig. 4.2, but use only one realisation of an underlying light-curve pair for each AGN, and compare it to the first of the light-curve realisations of the previous AGN, represented by the top row of Fig. 4.2. The results for all three AGN is shown in Fig. 4.3, where the rows this time represent AGN from different parts of parameter space, instead of different light-curve realisations. Similarly to the result for multiple realisations of a single AGN, Fig. 4.3 shows a tendency of larger deviations from the underlying lag values and higher uncertainty values in the bottom right corners of the heatmaps, representing light-curves with a lower sampling.

It should be noted that some of the lag recoveries for the window-functions representative of OzDES RM can be considered problematic, which is in accordance with the predictions of [King et al. \(2015\)](#), who estimated a $\sim 35\text{-}45\%$ success rate for individual lag recovery for OzDES RM. Additionally and importantly, the regions surrounding these window-functions, especially in direction of lower spectroscopic cadence, yield increasingly problematic lag recoveries. We interpret this as OzDES RM being representative of a minimal window-function density required for reliable lag recovery. In particular, considering the large number of highly deviating values for spectroscopy window-functions G, H, and I, Figs. 4.2 and 4.3 suggest that the emission-line region should not be observed less frequently than once a month.

4.2 The Impact of Cadence and Observing Season Length

For the purposes of planning future RM surveys, a further investigation of the window-function is worthwhile. In Sec. 4.1 we studied the impact of progressively lowering the sampling of the light-curves on lag recovery. A deeper examination of the impact of the window-function requires investigation of the frequency of observations and the length of seasonal gaps separately. Such an investigation has previously been performed by [King et al. \(2015\)](#), however, we wish to revisit the analysis due to the inconsistency between the success-rate predicted by [King et al. \(2015\)](#) and the challenges we have faced in lag recovery, as demonstrated by [Hoormann et al. \(2019\)](#) and this work.

The analysis performed by [King et al. \(2015\)](#) was based on an improvement to OzDES RM, where additional observing points were added to a pre-existing window-function. We expand on their analysis by not only evaluating improvement scenarios, but also scenarios where the window-function is modified by redistributing the observations, without changing their total number. A parallel study of the impact of cadence and observational season length where the total number of points can be left the same or increased will provide a broader picture of the effect the observational frequency and seasonal gaps have on lag recoverability.

Following [King et al. \(2015\)](#) we commence our analysis by comparing the results from fidu-

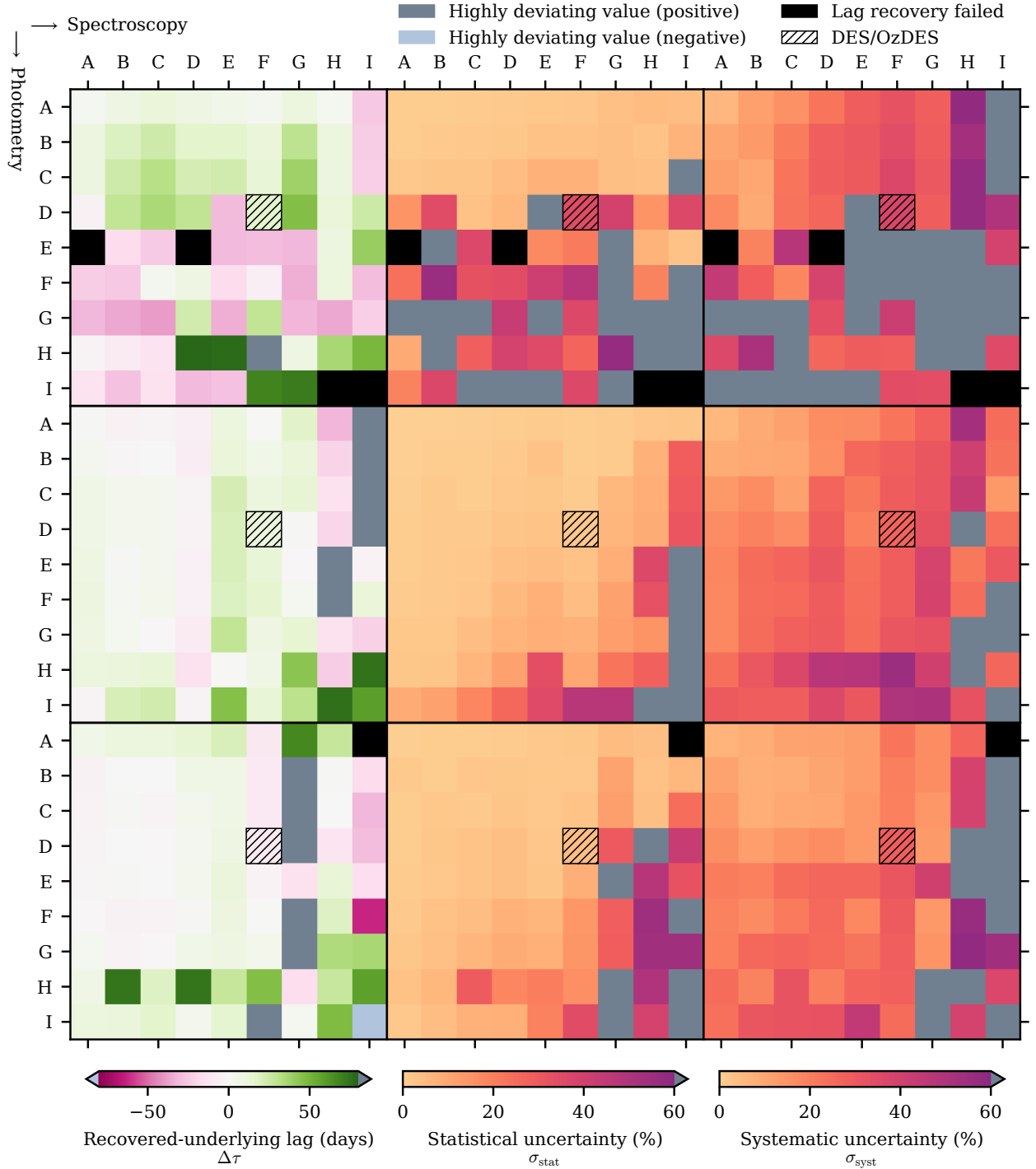


FIGURE 4.3: As in Fig. 4.2, but with the rows showing the lag recoveries for three different mock AGN, denoted by the black markers in Fig. 4.1. The AGN represent different areas of the OzDES parameter space, starting with the results for the AGN with the lowest redshift at the top, and continuing to the AGN with the highest redshift at the bottom.

cial window-functions to window-functions which have been improved. Since the survey strategy of OzDES was found to border on minimal sampling required for successful lag recovery in Sec. 4.1, we utilise window-functions based on the DES and OzDES survey strategies as our fiducial window-functions. The sampling of the emission-line light-curve, represented by the spectroscopy, is increased by extending the observational season length, raising the cadence, and a combination of the two. We allow the photometry window-functions, sampling the continuum light-curve, to have a constant cadence throughout the experiment, but change the length of the observational season to match the spectroscopy sampling. We apply the window-functions to a set of 250 mock light-curve pair realisations based on the same underlying properties, and study the resulting distribution of lag recoveries, shown on the left hand side of Fig. 4.4. The results for the fiducial window-functions (top left) are compared to the results where the sampling has been altered to

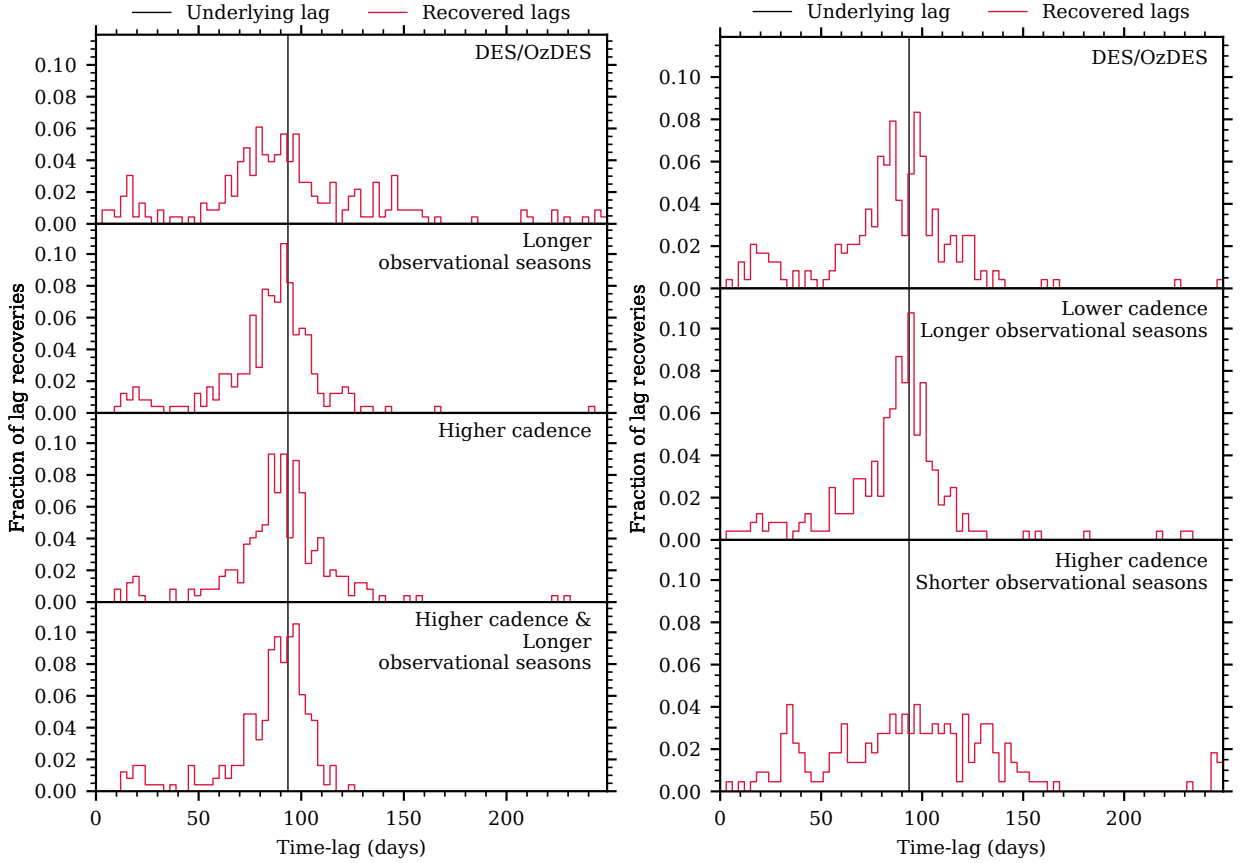


FIGURE 4.4: A comparison of lag recoveries for different survey realisations. Each subplot shows the distribution of lag recoveries for 250 light-curve pair realisations of a single AGN probed with the same window-function. The top subplot on each side represents the distribution of lag recoveries achieved when probing the light-curves with window-functions representative of DES and OzDES survey strategies. On the left hand side we compare what is expected from DES/OzDES to what we could expect to achieve, should it be possible to extend the observational seasons, perform more frequent observations, or a combination thereof. On the right we compare the performance of a DES/OzDES-like set of window-functions to surveys where the cadence and observational seasons need to compromise to achieve an approximately equal number of spectroscopy observations to that expected by OzDES.

lengthen the observational seasons (second from the top on the left), where the sampling cadence was increased (second from the bottom on the left), and where the sampling was increased through a combination of higher cadence and extended observational seasons (bottom left). It is clear that any increase to the sampling improves the lag recovery. However, the results for window-functions where an extension of the observing season was employed yield a more accurate and precise lag recovery distribution than when sampling is increased through a higher cadence. We are led to the same conclusion as King *et al.* (2015); that any additional observational time should be focussed on extending the observational season rather than increasing the cadence.

To expand our analysis we consider a scenario where the number of observations cannot be increased, and a compromise between cadence and observational season length must be found. We again use DES/OzDES strategies to model fiducial window-functions, then adjust the length of the seasonal gaps and the cadence of observations during the observing seasons such that the overall number of emission-line light-curve points remain close to constant. The continuum observations are left with their cadence unchanged, but have their observational seasons shortened or extended to match the emission-line light-curve. The right hand side of Fig. 4.4 shows the distributions of lag recoveries for 250 mock light-curve pair realisations, with the fiducial window-function (top right) compared to a survey implementation where the cadence is lowered to allow for longer observational seasons (middle right), and compared to a survey implementation where the observational seasons are shortened to allow for higher cadence (bottom right). We observe an improvement in accuracy and precision of the lag recovery for the window-function with longer observational seasons compared to the fiducial window-function, despite a lowered observation cadence. A greater impact is to be seen for the the window-function with higher cadence and longer seasonal gaps, where the precision of lag recovery has reduced significantly. It is clear that the seasonal gaps truly have a greater impact on lag recoverability, and might indeed be the reason behind the frequent problems to be found on the far right hand side of the heatmaps in Figs. 4.2 and 4.3.

4.3 The Problem With Seasonal Gaps

In accordance with the results in Sec. 4.2 and Fig. 4.4, King *et al.* (2015) predicted an improvement in lag recovery for AGN probed with window-functions based on survey strategies striving towards a closure of the seasonal gaps, in particular for AGN with lags close to $365 \cdot n_{\text{odd}}/2$ days, where n_{odd} is an odd integer. With the OzDES RM survey strategy, such lags are anticipated to be difficult to recover, due to the small overlap between continuum and emission-line light-curve observations. To demonstrate this, we present two mock light-curves in Fig. 4.5. The continuum light-curves are the same in both plots, and the emission-line light-curves are created using a transfer-function of the same width, but centred around a different lag value. In a perfect scenario, observations of the light-curves are close to continuous during the observational seasons, and we would observe the parts of the light-curves covered by the shaded regions of Fig. 4.5.

Due to the AGN time-lag, and its consequent shift of the light-curves relative to one another, our

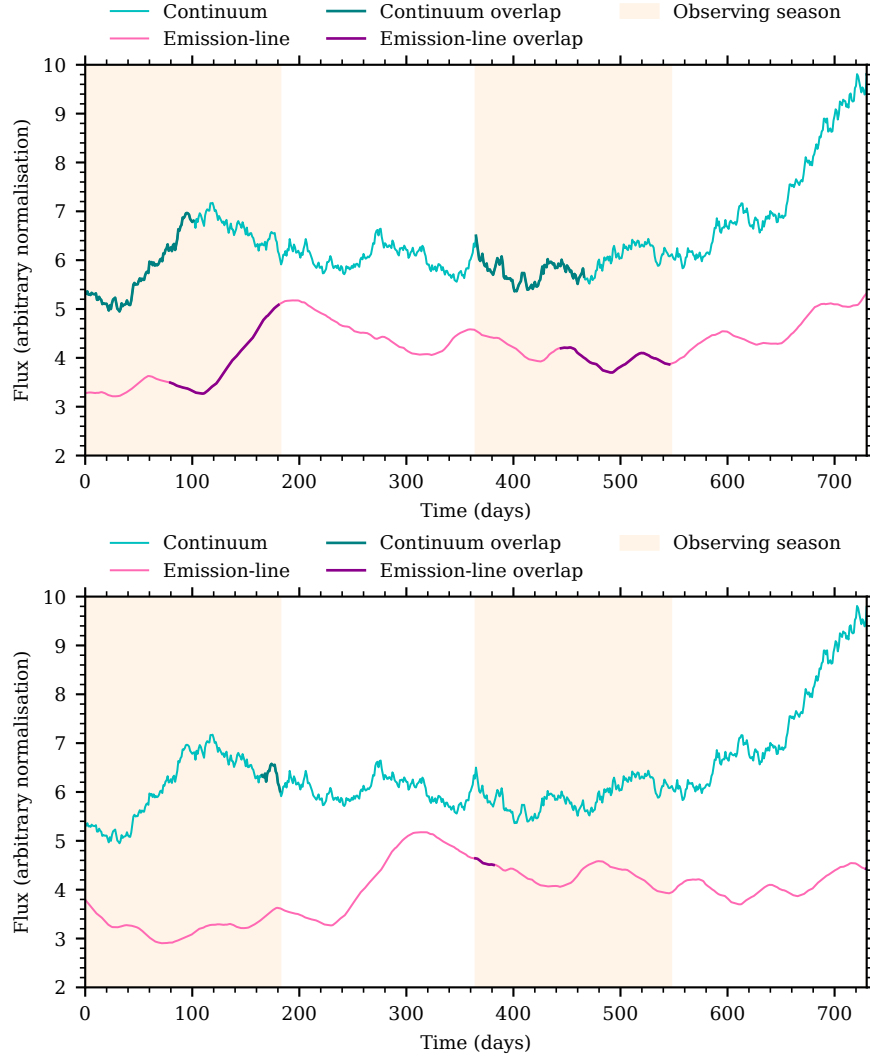


FIGURE 4.5: Mock continuum and emission-line light-curves in the observed frame. Only two years worth of light-curves is shown. The emission-line light-curve is smoothed by the same amount in each sub-plot, but is shifted by a different amount in the top subplot compared to the bottom. We highlight the sections of the light-curves which are observed for both the continuum and emission-line region within the observing season using a darker colour. The amount of overlap is greater if the emission-line light-curve is shifted by an amount close to $n_{\text{even}}/2$ days, whereas a shift close to $n_{\text{odd}}/2$ days results in smaller overlapping regions.

observations of the continuum and emission-line light-curves correspond to different evolutionary stages of the accretion disc. Specifically, the continuum light-curve is going to provide information which is not covered by the emission-line light-curve due to lack of observations during the seasonal gap, and vice versa. In Fig. 4.5 we differentiate the overlapping regions of the light-curves from the non-overlapping areas by using darker colours to indicate the continuum (emission-line) light-curve segments observed and corresponding directly to a segment observed for the emission-line (continuum) light-curve.

It is (to first order) only measurements of the light-curves marked with darker colours that

contain information which can be used to determine the time-lag of the AGN. While the remaining light-curve measurements are used when calculating the cross-correlation between the light-curves, they are from regions of the light-curve which are not expected to correlate, and as such they do (to first order) not contain information which actively contributes to increasing the cross-correlation signal at the value of the AGN time-lag. The two light-curve pairs shown in Fig. 4.5 illustrate how a difference between lags close to $365 \cdot n/2$ days for even and odd values of n affects the information available to produce relevant cross-correlation signal. In the top plot a lag of 80 days is used, yielding a lag close to $356 \cdot n_{\text{even}}/2$ days, whereas the lag for the bottom plot is 200 days, and thus closer to $365 \cdot n_{\text{odd}}/2$ days. For the light-curve pair separated by 80 days, a large portion of the continuum (emission-line) light-curve observed has a complementary observation in the emission-line (continuum) light-curve. A higher number of complementary, overlapping observations implies a larger amount of observations boosting the cross-correlation signal at the correct time-lag value. Conversely, a small overlap between the light-curves, as for the light-curves with a 200 day lag, will decrease useful information, thus complicating the lag recovery, especially in terms of precision.

The bottom plot of Fig. 4.5 also illustrates another problem; careful study of the darker, overlapping region of the light-curves shows a discrepancy between the continuum and emission-line signal. While the dark segment of the continuum light-curve forms a peak, the smoothing by the transfer-function has altered the corresponding segment of the emission-line light-curve to be smooth, and resemble more of a dip than a peak. A calculation of the cross-correlation between these segments would add negatively to the signal for this lag value, despite being the correct answer, thus complicating the lag recovery. This example illustrates that a disparity between overlapping light-curve segments – be it due to the inherent properties of the light-curves (such as smoothing by the transfer-function, as it is in this case), or caused by errors or uncertainties in our measurements – will influence the cross-correlation function to disfavour the corresponding lag value. In such a case the cross-correlation function will deem the underlying lag value inappropriate, and statistical leverage may favour a lag value corresponding to the light-curves having no overlapping segments ($365 \cdot n_{\text{odd}}/2$ days, with n_{odd} having the specific value of $n_{\text{odd}} = 1$ for this particular scenario).

The problems of lag recovery for AGN with lags close to $365 \cdot n_{\text{odd}}/2$ days in the observed frame provides insight to our analysis in Chap. 3. Our null result could in part be caused by the two problematic behaviours demonstrated in this section; the lack of first-order contribution to cross-correlation signal at the lag value by these sources, together with an increased possibility of correlation signal at lags corresponding to non-overlapping light-curves. By excluding AGN likely to interfere with successful lag recovery, it is possible the analysis of Chap. 3 could have provided us with additional lag recoveries for the CIV emission-line, and a new measure of the CIV $r - L$ relationship. An analysis of sources to determine their appropriateness for stacking purposes would require extensive simulations of the parameter space. A range of different $r - L$ relationships would need to be tested, since this relationship will determine which AGN are likely to have lags corresponding to $365 \cdot n_{\text{odd}}/2$ days in the observed frame. Furthermore, an extensive testing of selection bias would have to be performed, to ensure validity of results.

The primary contribution to cross-correlation signal at the AGN lag value is the time-lag itself, which is seen through light-curve overlap, as demonstrated in Fig. 4.5. However, the time-lag information can be propagated further by the width of the transfer-function, which will cause a phase shift of the lag information. Furthermore, information can be drawn from the damping time-scale τ_d , which affects long-term variation in both continuum and emission-line light-curves. The impact of these secondary effects is illustrated in Fig. 4.6, where we show the same light-curve pair as in the bottom plot of Fig. 4.5, but over the course of five years. The amplitude of the continuum light-curve is relatively low and constant throughout the first two observing seasons, but the third observing season sees the decline after an amplitude peak significantly above what was observed during the first two seasons. For the emission-line light-curve we observe a relatively steady second observing season, followed by a rise in amplitude throughout the third season. Knowing the continuum light-curve must have increased after the second observational season to decline throughout the third gives us some indication of the shift between the light-curves to allow the features to align. This information will be captured in the cross-correlation function, but will unfortunately only be a secondary effect. To achieve a stronger cross-correlation signal at the time-lag value, and to locate it more precisely, it is necessary to utilise the information of the overlapping light-curve segments directly. Furthermore, caution must be shown in interpretation of lag recovery for this type of sources, as the time-scale identified by the correlation function may tend towards the observational frequency or the damping time τ_d instead of the lag.

It is clear from the analysis in this section that AGN with lags of order $365 \cdot n_{\text{odd}}/2$ days pose challenges to RM programs with survey strategies similar to OzDES RM due to the gaps between

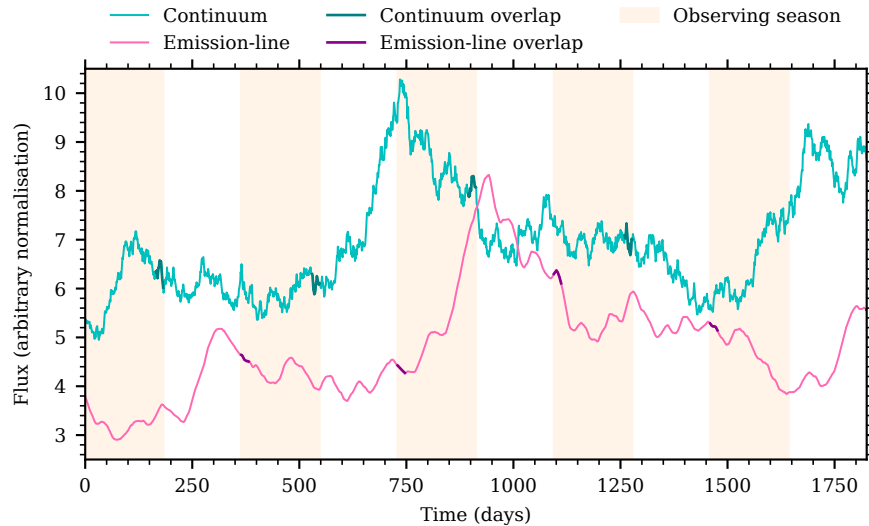


FIGURE 4.6: Continuum and emission-line light-curves in the observed frame. The mock light-curve pair is the same as that in the bottom plot of Fig. 4.5, but shown over a period of 5 years. While the lag, which is close to $n_{\text{odd}}/2$ years, is limiting the amount of direct overlap between the light-curves, the general shape of the light-curves may be used to infer some information about the phase shift between the light-curves.

our observational seasons, and consequently, the small amount of overlapping data to construct cross-correlation signal at the value of the AGN time-lag. Longer seasonal gaps will only exacerbate the lack of overlap between light-curves, forcing lag recovery to be based on secondary effects. The analysis in Chap. 3 could have benefited from taking the findings in this chapter into account by adjusting the choice of the binning to exclude AGN which may have had a negative impact of the stacked lag recovery. However, our choice of binning cannot accommodate for the results of Chap. 3 alone; the difference between lag recovery success for mock and observed data implies the need of investigation of the assumed DRW model for the continuum light-curve.

While a pre-selection of sources to exclude AGN with lags close to $365 \cdot n_{\text{odd}}/2$ days can steer the lag recovery towards a higher success-rate, such a selection introduces a potential bias based on pre-existing $r - L$ assumptions. Designing RM programs such that longer seasonal gaps can be avoided will not only prevent such a potential bias, but ensure more overlap between light-curves for AGN with all lag values.

4.4 Conclusions and Impact on Current and Future Surveys

While a $\sim 35\text{-}45\%$ success-rate for individual source lag recovery was predicted by [King *et al.* \(2015\)](#) for OzDES RM, both individual lag recovery and group analysis through stacking of OzDES RM AGN have hitherto proven more challenging. Through this chapter we have demonstrated some of the challenges of an RM program with simulations, and shown the possibility that the survey strategy of OzDES RM may function as a baseline requirement for reliable lag recovery, assuming the likely overly positive outlook provided by simulations. Other recent RM programs measuring AGN lags for the C IV emission-line have been published by [Lira *et al.* \(2018\)](#) and [Grier *et al.* \(2019\)](#), both based on survey strategies differing significantly from that of OzDES RM and from each other. SDSS-RM obtained a total of 68 spectroscopy epochs over four observational seasons, of which nearly half were performed over the first year of observations, and the remaining years had 12 epochs each ([Grier *et al.* 2019](#)). The number of epochs correspond to a sub-weekly observational cadence for the first year, and bi-monthly for the remaining three. The observing seasons of SDSS-RM are similar to that of OzDES RM, with seasonal gaps of 6 months each year. Based on the analysis in Sec. 4.1 we can expect the lag recovery from SDSS-RM to be somewhat more successful than for OzDES RM given a higher cadence, however, due to the similarity in seasonal gaps, the difference should not be drastic. [Lira *et al.* \(2018\)](#) represent a modification in survey strategy in opposite direction; their spectroscopic measurements average out to between one to two observations each year. From Sec. 4.3 we can infer that while lag recoveries with such a survey strategy cannot be dismissed, one should be careful in the interpretation of the results, as they are based primarily on secondary effects, and likely to only give an approximate interpretation of the real physics at play.

With a number of large-scale RM programs planned for the near future ([Kollmeier *et al.* 2017, 2019](#); [Swann *et al.* 2019](#); [The MSE Science Team *et al.* 2019](#)), it is important we understand how to plan efficient RM programs, especially since telescopes at which industrial scale RM will be viable

are already being built (ESO 2011; TMT Observatory Corporation 2007, 2015; GMT O Corporation 2012; Seery & Smith 1998; Sabelhaus & Decker 2004). The lessons we are learning with first generation bulk RM programs such as OzDES RM and SDSS-RM are crucial to streamline the future decades of astronomy research. We have seen the impact of the window-function on lag recoverability, and the importance of closing seasonal gaps to attain reliable, high-quality RM results. With the knowledge of key details to successful lag recovery future RM programs can alter their strategies to make the most of their observations, and advance not only the field of RM, but also the applications thereof.

5

Conclusion

Since their discovery, active galactic nuclei (AGN) have been a focal point of research in many astronomical fields. Their high luminosity and abundance over a wide range of redshifts, ranging from the local Universe to $z \geq 7.5$ (Bañados *et al.* 2018), make them ideal for studying the evolution of properties of interest over cosmological time. The method of reverberation mapping (RM), originally used for studies of the innermost regions of AGN (Blandford & McKee 1982), is useful not only for the evolution of black holes and the galaxies in which they reside (Kormendy & Ho 2013), but also in cosmology through future studies of dark energy, and the evolution thereof (Watson *et al.* 2011).

For a long time RM was applied to recover time-lags and obtain black hole mass estimates for a relatively small number of AGN, almost exclusively in the local universe (see compilation of 62 AGN by Bentz & Katz 2015). The number of AGN with RM results has since been increasing dramatically, mainly due to new, large-scale multi-object spectroscopy surveys, which target a large number of objects over extended periods of time. Sloan Digital Sky Survey Reverberation Mapping (SDSS-RM, Grier *et al.* 2017b, 2019) and Australian Dark Energy Survey Reverberation Mapping (OzDES RM, King *et al.* 2015; Hoormann *et al.* 2019) have both been targeting high numbers (~ 800) of AGN over a broad range of redshifts ($0.1 < z < 4.5$). In this thesis we analysed the survey strategy of OzDES RM, and used it to investigate the statistical approach to RM through stacking put forward by Fine *et al.* (2012) through simulated and observational data. Despite previously demonstrated success of a stacking approach to RM using the DCF by Fine *et al.* (2012, 2013), the application of this method to observed OzDES RM data led to what we have interpreted as a null result. It should be noted that it is possible the lag recoveries found in Sec. 3.3 could reflect the physical reality

of the observed AGN, and the discrepancies between expected and achieved results are merely an effect of an intrinsic scatter about the $r - L$ relationship for the C IV emission-line. We choose not to rely on this assumption, since the recovered lags seem to not seem to have a random scatter, but rather follow a specific trend, trend perpendicular to the $r - L$ relationship. As we cannot explain the selection bias that would result in this physical phenomenon, we refrain from claiming reliable lag recovery for this AGN sample at this point in time.

The disparities found between our results using simulations and observed data forces us to reassess the survey strategy adopted by OzDES RM, and previous forecasts for program success rates. Such information is of great importance for upcoming surveys planned for the next decades, when surveys led by SDSS-V, the Time-Domain Extragalactic Survey (TiDES), and the Maunakea Spectroscopic Explorer (MSE) will have dedicated programs to investigate thousands of AGN for RM purposes (Kollmeier *et al.* 2017, 2019; Swann *et al.* 2019; The MSE Science Team *et al.* 2019).

5.1 Realistic Nature of Simulations

One of the major findings in this thesis has been a discrepancy between the predictions of our simulations and the results from observational data. In Chap. 3 we used simulations, generated using a damped random walk (DRW) to model the continuum light-curve, and a top-hat transfer-function to obtain the emission-line light-curve, to show that lag recovery for OzDES RM could be significantly improved through stacking. However, when the stacked lag recovery algorithm was applied to observed data, we achieved a null result due to low levels of correlation between the ingoing continuum and emission-line light-curves, likely partially caused by the long seasonal gaps in the OzDES RM window-function (see Chap. 4). The disparity in the strength of the lag recovery signal between simulations and observational data suggests simulations must be improved to better reflect reality.

To improve simulations, and study the impact of the many parameters describing our data on lag recovery, future work should investigate the underlying assumptions made, and repeat the analysis with mock data generated in alternative ways. In particular, attention should be paid to the following:

1. The discrepancy between lag recovery results for simulated mock data and observed light-curves from OzDES RM suggests the DRW model may be a poor representation of the continuum variability properties of the OzDES RM sample. Inconsistencies between this model and observational data were found already by Mushotzky *et al.* (2011), and the DRW model has continued to be challenged since (*e.g.* Caplar, Lilly & Trakhtenbrot 2017; Kozłowski 2017). It is clear that alternative continuum variability models should be sought after and utilised. Starkey, Horne & Villforth (2016) provided an alternative approach in the CREAM (Continuum REprocessed AGN Markov Chain Monte Carlo) method, by modelling continuum light-curves based on a lamp post thermal reprocessing model (see *e.g.* Nayakshin & Kazanas 2002; Cackett, Horne & Winkler 2007). Other approaches to continuum modelling are also underway

(Tachibana *et al.* 2020; Hu & Tak 2020).

2. A top-hat transfer-function, chosen for our work based on the discussion in Sec. 2.2, may be an overly simplified approach to emission-line light-curve generation for realistic mock data. Convolution with a top-hat function does provide maximum smoothing at all non-zero values of the transfer-function, however, it does not represent a physically realistic scenario. It is possible a transfer-function would be better described by an asymmetric distribution, and the distribution would almost certainly have tails on both ends instead of rigid ends. While the nature of transfer-functions remains enigmatic (Peterson 1993; Horne *et al.* 2004; Mangham *et al.* 2019), it is worth investigating whether a different choice of transfer-function will provide a more realistic picture of mock light-curves, and affect the results in this thesis.
3. In addition to challenging the DRW model and top-hat transfer-function, future work could also investigate the effect of uncertainties used to make the data more realistic. The mock data generated for our simulations were modified by adding Gaussian noise and associated uncertainties based on conservative estimates from observational data. King *et al.* (2015) did, however, argue that some non-Gaussianities should be added to mock light-curves representative of OzDES RM for realism purposes, despite OzDES data residuals being Gaussian in form. By generating mock data in a range of different ways, future analysis can show which criteria must be satisfied for methods such as stacking to be of use.

5.2 Impact of Lag Recovery Methodology

The lag recovery method lies at the very heart of RM. Correct AGN lags are necessary for the measurements of the geometrical structure of the innermost regions of AGN, and for application of RM to other fields. In this thesis we have used the discrete cross-correlation function (DCF) introduced by Edelson & Krolik (1988), making only minor adjustments in normalisation to account for the quality of OzDES RM data. The DCF represents a natural choice for a first attempt at a stacking analysis (see discussion in Sec. 2.3.1). We applied the DCF to OzDES RM data, expecting the major result of this thesis to be an addition of lag recovery points to the C IV $r - L$ relationship. Instead, we achieved a null result due to lack of correlation signal in the stacked DCFs.

Despite its positive qualities, the DCF may represent too conservative of a choice for a lag recovery algorithm when applied to data of OzDES RM quality. For low volumes of data, approximation of light-curves by interpolating between observations provides valuable additional information to the extent where the approximation can be seen as reasonable. To increase our chances of successful lag recovery, we could thus have considered a middle ground between the DCF and interpolated cross-correlation function (ICCF), simultaneously applying the aspects of averaging from the DCF and the interpolation from the ICCF. Additional future work should consider the following:

1. Our null result for stacking of observational data may indicate that a more advanced methodology is required for OzDES RM. An improvement to the DCF was suggested by Alexander

(1997) in the form of the z -transformed discrete correlation function (ZDCF), which is based on the traditional DCF methodology, but bins individual cross-correlation values based on equal population instead of equal time differences. The ZDCF has successfully been used for stacking (Li *et al.* 2017), albeit with the drawback of requiring the stacking to be performed in observed frame instead of rest frame to avoid interpolation and re-binning. The method can, however, still be useful for dense regions in parameter space, and effort can be made to improve the methodology for the less populated areas.

2. The Markov chain Monte Carlo (MCMC) based algorithms **JAVELIN** (Zu, Kochanek & Peterson 2011) and **CREAM** (Starkey, Horne & Villforth 2016) have allowed lag recovery for instances where cross-correlation based methods have failed or had significant uncertainties, and the results from these algorithms are thought to be preferential over the conservative results from cross-correlation functions, given the more sophisticated algorithm. While we decided against using these algorithms for our initial stacking analysis, based on the strengths and weaknesses discussed in Sec. 2.3, our lag recovery method of choice yielded a null result for observational data, suggesting a more sophisticated lag recovery method is needed for data of OzDES RM quality. **JAVELIN** and **CREAM** both represent natural choices for the design of a more advanced stacking procedure in the future.
3. One of the downsides of a cross-correlation function based stacking analysis is the difficulty of distinguishing different broadening effects when interpreting the width of the peak associated with lag recovery. Brewer & Elliott (2014) addressed this problem by introducing a hierarchical Bayesian approach to stacking for RM, in which the broadening caused by using objects with inherently different lags could be detangled from the broadening caused by signal uncertainty. Provided the potential issues with **JAVELIN** and **CREAM** can be resolved, an important step in future stacking analysis will be the integration of these algorithms with hierarchical models to maximise scientific information in the lag recovery signal.

5.3 The Future of RM Surveying

In this thesis we have used simulated mock data to forecast and contextualise results for OzDES RM. We have applied our chosen methodology to observational data, finding a null result for RM in bulk in Chap. 3, in conflict with the predictions of our simulations. In Chap. 4 we explored survey strategy as one possible factor contributing to the discrepancy between simulations and observational results, and found seasonal gaps to have a significant, negative impact on lag recovery. The effect of seasonal gaps would have had a varying level of impact on former RM results in literature; seasonal gaps are less likely to affect AGN at lower redshifts and with shorter lags, which were the more common targets prior to the use of multi-object spectroscopy for RM purposes (see e.g. Peterson *et al.* 2004 and AGN compilation in the Bentz & Katz 2015 AGN database). To correctly recover lags for AGN with shorter lags, survey cadence is of higher importance, to avoid lag recovery based on secondary

effects. Since OzDES RM is one of the first RM programs using multi-object spectroscopy, and large amounts of the observed data remain to be analysed, we observe the following regarding the near future of OzDES RM and RM programs with similar survey strategies:

1. The discrepancy between lag recovery results for simulated and observed data led us to analysing the impact of the window-function on lag recovery, however, the results of Chap. 3 and Chap. 4 should be interpreted as independent results. While these effects influence each other, with the possibility of exacerbating each other's negative effects, they are each important, and require an investigation of their own. Simulations should be improved to better reflect reality regardless of window-functions (see Sec. 5.1), and simulations should not prevent survey strategies from being modified and improved to increase the chance of lag recovery success for observational data.
2. The window-function analysis detailed in Chap. 4 reinforced the findings of [King *et al.* \(2015\)](#) – that RM observations benefit from the shortening of (the largely inevitable) seasonal gaps to the extent possible. We also took care to thoroughly highlight the challenges of lag recovery by illustrating how the seasonal gaps effectively remove data useful to creating cross-correlation signal. Although sophisticated lag recovery algorithms such as those discussed in Sec. 5.2 may have comparatively less problems with lag estimation, we recommend showing care in the interpretation of RM results of data with long seasonal gaps.
3. OzDES RM has recently been extended to the end of 2020. This program extension will expand the observational baseline for our AGN, thus increasing the possibility of successful individual and stacked lag recovery for the AGN with the longest time-lags. The program extension will be particularly useful for the most distant targets, whose lags are inherently long due to the natural choice of high-luminosity sources, but are made longer by cosmic time-dilation. We can expect a higher rate of successful lag recoveries for the C IV emission-line, using both a stacked and individual lag recovery approach. It should be noted that this extension will be useful by increasing the volume of observations, yielding a predicted increase in signal-to-noise ratio for targets with long lags. The longer observational baseline will, however, not resolve the problems caused by long seasonal gaps, since the program extension follows the same survey strategy as the general OzDES survey.

In addition to the short-term implications of our work on OzDES RM, the analysis in this thesis is important for the coming evolution of the field of RM in this coming decade. The impact of the window-function, and the seasonal gaps in particular, is of great importance for the planning and execution of future RM programs. A number of large-scale multi-object RM programs are planned for the coming decade; the Black Hole Mapper (BHM) survey as a part of SDSS-V ([Kollmeier *et al.* 2017, 2019](#)), the TiDES-RM program to be performed at the 4-metre Multi-Object Spectroscopic Telescope (4MOST, [Swann *et al.* 2019](#)), and an RM program planned by the MSE Collaboration ([The MSE Science Team *et al.* 2019](#)). In addition to spectroscopic surveys, photometric surveys –

such as the Legacy Survey of Space and Time (LSST) at the Vera C. Rubin observatory – are likely to participate and provide additional data for RM purposes (LSST Science Collaboration *et al.* 2009). The survey strategies adopted by these programs will heavily influence their results, and ability to reach their set out goals. TiDES-RM and MSE both highlight using RM to determine distances for redshifts $z > 2$ as one of their science goals. Even targeting hundreds or thousands of AGN, as is planned for these surveys, reliable distance measurements will only be possible if the surveys are executed with appropriate strategies for cadence and observing seasons. We strongly recommend future RM programs to reassess their survey strategies, and explore options allowing for extensions of the observational seasons to maximise the scientific value of their observations. If appropriate changes can be made now, the field of RM and all the applications thereof can develop faster without the need to wait for the announcements of future surveys and telescopes.



Individual Lag Recoveries Using Standard Bins

Individual lag recoveries for each of the bins B01-B13. The lag recoveries are presented as a vertical line together with an uncertainty marked as a surrounding shaded region representing the uncertainty of the recovery. The lag with its total uncertainty is shown together with the stacked DCF and its fitted Chebyshev function in the top section of each plot. Below it are the histograms representing the alternative lag recoveries, used to calculate the statistical and systematic uncertainties. The uncertainties are indicated by highlighted regions overplotting the corresponding histograms.

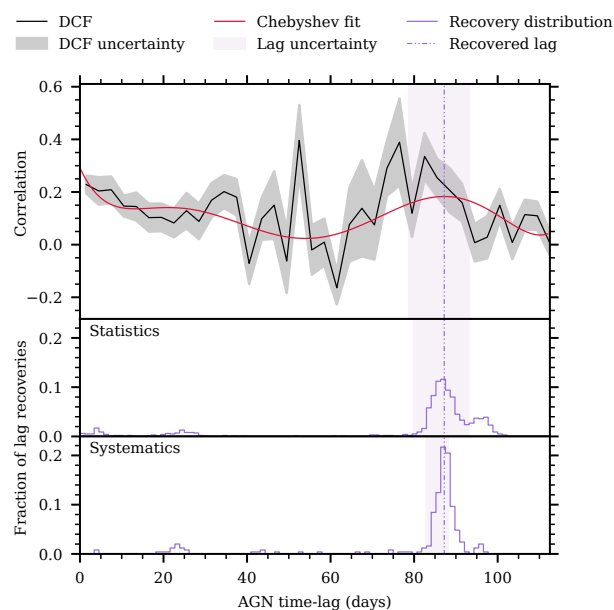


FIGURE A.1: Lag recovery for B1 based on DCF and Chebyshev function, together with the associated histograms used for calculation of statistical and systematic uncertainty.

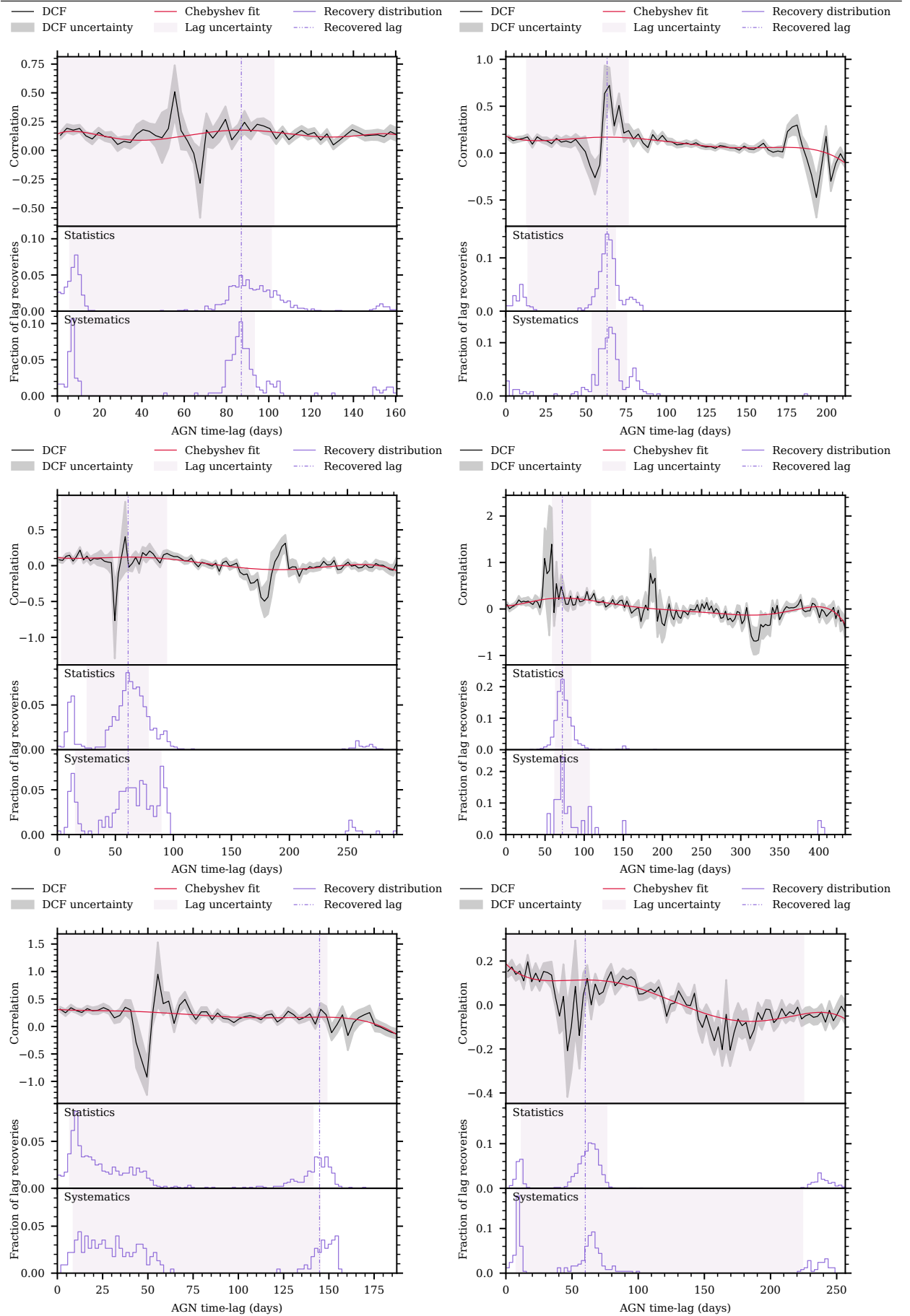


FIGURE A.2: As in Fig. A.1, for bins B02 (top left) to B07 (bottom right), reading horizontally.

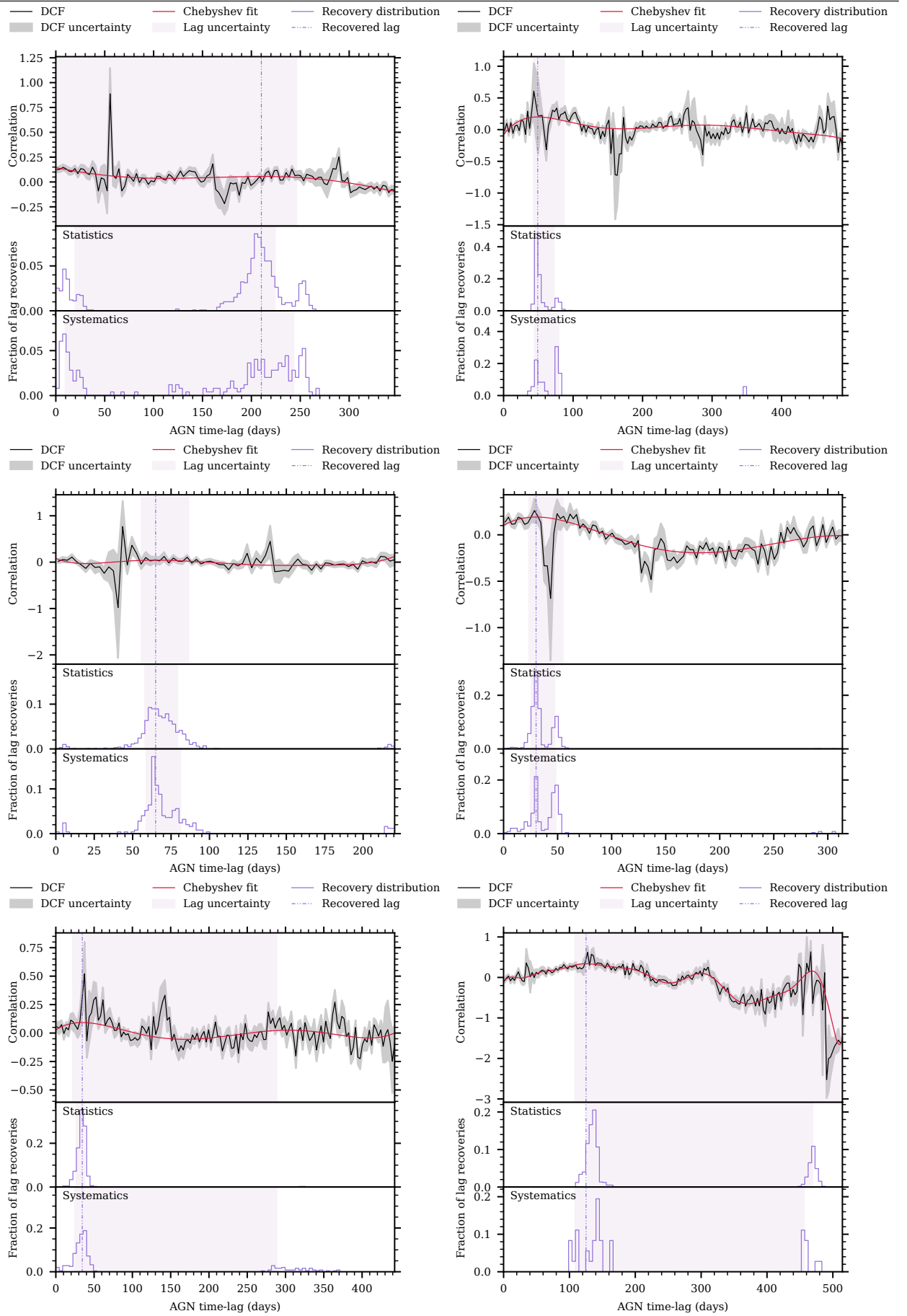


FIGURE A.3: As in Fig. A.1, for bins B08 (top left) to B13 (bottom right), reading horizontally.

B

Individual Lag Recoveries Using Larger Bins

Individual lag recoveries for each of the bins B01'-B07'. The lag recoveries are presented as a vertical line together with an uncertainty marked as a surrounding shaded region representing the uncertainty of the recovery. The lag with its total uncertainty is shown together with the stacked DCF and its fitted Chebyshev function in the top section of each plot. Below it are the histograms representing the alternative lag recoveries, used to calculate the statistical and systematic uncertainties. The uncertainties are indicated by highlighted regions overplotting the corresponding histograms.

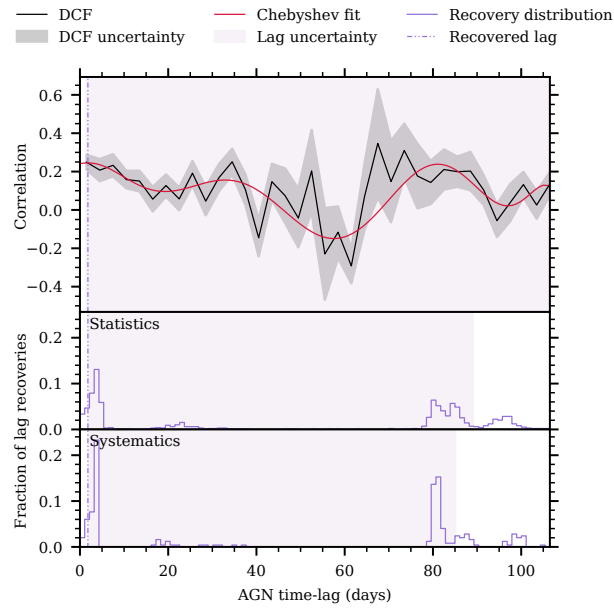


FIGURE B.1: Lag recovery for B01' based on DCF and Chebyshev function, together with the associated histograms used for calculation of statistical and systematic uncertainty.

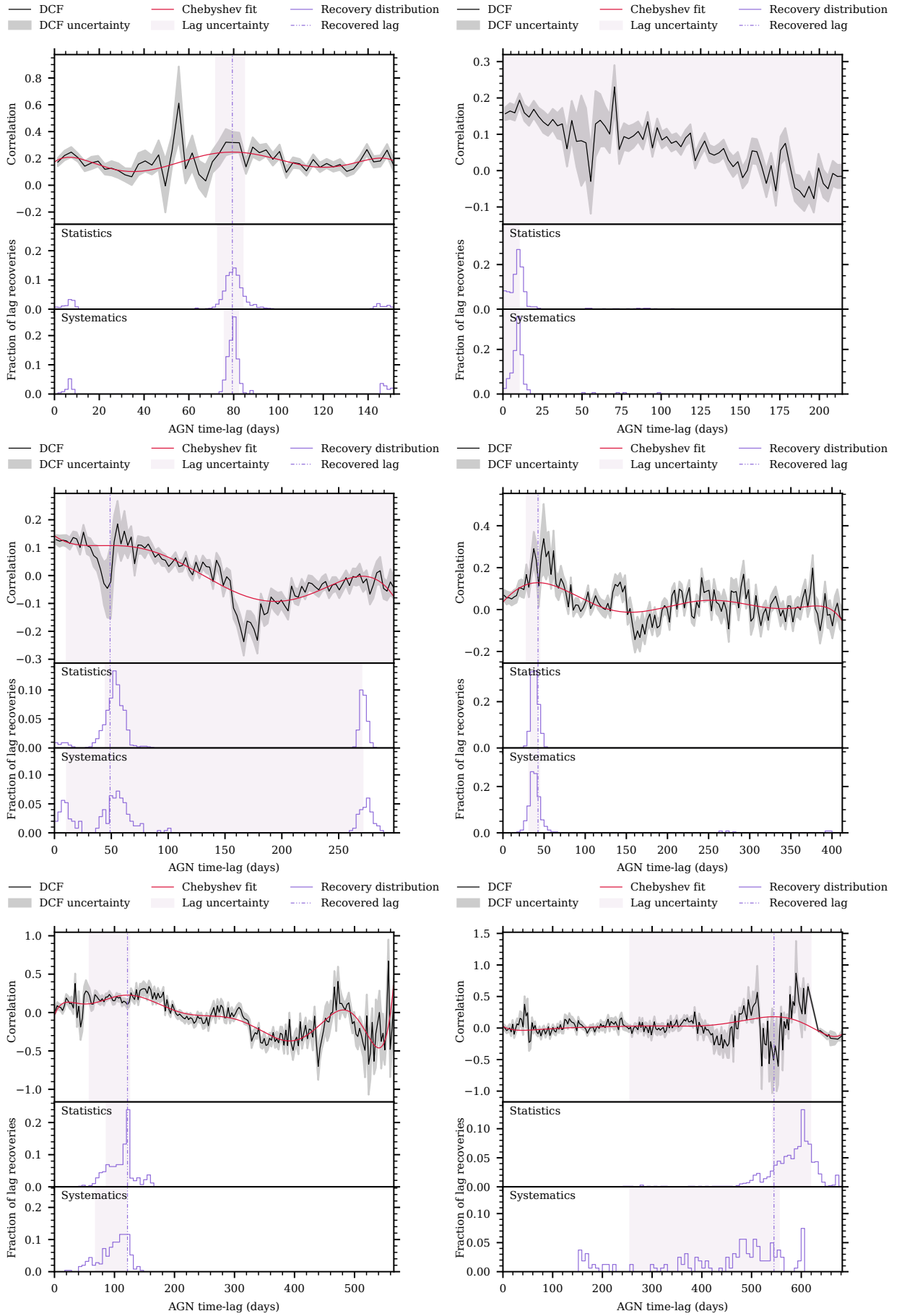


FIGURE B.2: As in Fig. B.1, for bins B02' (top left) to B07' (bottom right), reading horizontally.

Afterword

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- *Mozzarella*, the author's kitten

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