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Inquiry Editors

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Message from the Vice Chancellor of the Division of Research and Innovation

Welcome to the new issue of the Inquiry Journal, back after nearly five years of dormancy! These unprecedented times have adversely impacted the U of A and the regular publication of Inquiry Journal. I'm glad that we are moving past this era, and I'm excited that we are back on track again.

The Office of Undergraduate Research, in the Division of Research and Innovation, has taken up the revival of Inquiry Journal as a top priority. Moving forward, we hope to regularly publish two issues (May/June and November/December) of Inquiry Journal every year to showcase the excellent research conducted by undergraduate students on our campus to further promote the U of A research mission. I envision Inquiry Journal to be a platform cultivating collaboration amongst our bright undergraduate student population, dedicated faculty, and university administration across campus to foster undergraduate research. The articles published in this issue of Inquiry Journal are a testimony to both the high quality of research undertaken by our undergraduate students and the interdisciplinary research collaboration between our students and faculty. More importantly, I envision Inquiry Journal as a valuable avenue for undergraduate students to get a glimpse of the logical steps involved in the eventual publication of articles in peer-reviewed journals. In this context, I encourage both the undergraduate students and their faculty mentors to consider Inquiry Journal as a vehicle to publish their best research findings.

I congratulate the Editors of Inquiry for re-invigorating the Journal, and I anticipate that additional exciting new features will be incorporated in the future issues of Inquiry. I also want to thank Professor Suresh Thallapuranam for his excellent leadership in the Division to make this renewal a reality. On a final note, I encourage all undergraduate students on this campus to actively engage in undergraduate research and explore opportunities for experiential learning. I eagerly look forward to reading about your fantastic scholarly contributions to the Inquiry Journal!

Editors' Note

Welcome to the new issue of the *Inquiry* Journal. It is really refreshing to have successfully weathered the challenges posed by the COVID pandemic. The papers published in this issue of the *Inquiry* Journal are a clear reflection of the hard work and dedication of the undergraduate students and their faculty mentors, who despite the obstacles faced, have managed to produce excellent research work. All manuscripts published in this issue of the *Inquiry* Journal have gone through a rigorous peer-review process and are an embodiment of the high quality of research undertaken by the undergraduate students on our campus. In addition, some of the papers published in this Issue clearly showcase the interdisciplinary nature of undergraduate research work embarked on by our students. We congratulate all students for their scholarly efforts and wish them continued success on their research path. We will continue to strive hard to publish top-notch undergraduate research while maintaining the ethical standards expected of a peer-reviewed Journal like Inquiry.

The publication of this issue of the *Inquiry* Journal would not have been possible without the help of several devoted faculty who dedicated their time to peer-review manuscripts submitted for publication. A lot of credit is also due to the undergraduate students at OUR, Ms. Sophia Nourani and Ms. Ashlyn Gibby, who have worked tirelessly with us to prepare this issue of I*nquiry*. Our special thanks also go to Drs. Chelsea Hodge and Jennie Popp who contributed the material, published as the Honors Corner, at very short notice. Last but not the least, we greatly acknowledge the help provided by Ms. Melody Herr and Ms. Cedar Middleton for working closely with us to get this Issue of Inquiry published in Scholarly Works in a timely manner. *Inquiry* Journal will be published twice a year (May/June and November/December) and we urge both undergraduate students and their faculty mentors to submit their best research for publication in Inquiry.

Suresh Thallapuranam, Ph.D and Shannon Servoss, Ph.D

Co-Directors, Office of Undergraduate Research
Division of Research & Innovation

Artificial Intelligence System for Automatic Imaging, Quantification, and Identification of Arthropods in Leaf Litter and Pitfall Samples

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Abstract

It is well known that arthropods are the most diverse and abundant eukaryotic organisms on the planet. Museum and research collections have huge insect accumulations from expeditions conducted over history that contain specimens of both temporal and spatial value, including hundreds of thousands of species. This biodiversity data is inaccessible to the research community, resulting in a vast amount of "dark data". The primary objective of this study is to develop an artificial intelligence-driven system for specimen identification that greatly minimizes the time and expertise required to identify specimens in atypical environments. Successful development will have profound impacts on both ecology and biodiversity sciences as it will increase the resolution for ecological studies and allow us to work through the backlog of insect collections, unlocking tremendous amounts of biodiversity data. Development of the system will address multiple challenges in deep learning, including problems associated with limited training data and moving from known domains into unknown. The cutting-edge AI solutions will be a final component in a smart specimen identification system scalable in multiple platforms and across geographic region.

Keywords:

Adversarial Training – Training a model using a discriminator and generator. The generator generates images while the discriminator determines which images are not close to the ground truth.
Domain Adaptation – Applying the knowledge of a deep learning model to a different domain.
Semantic Segmentation – Assigning a label to every pixel in an image.
Semi-supervised Learning – Training a model on labeled data, then using unlabeled data to improve the training results.

Profiles of the Authors

Pierce Helton is an undergraduate CSCE major at the University of Arkansas. He is working as a research assistant in Dr. Luu's CVIU lab. His research interests are Machine Learning, Deep Learning, and Computer Vision. Pierce has plans to work in the industry and potentially pursue a M.S. in Computer Science after earning his B.S.

Dr. Khoa Luu is an Assistant Professor and the Director of Computer Vision and Image Understanding (CVIU) Lab in Department of Computer Science and Computer Engineering (CSCE) at University of Arkansas, Fayetteville, USA. He is serving as an Associate Editor of IEEE Access Journal. He was the Research Project Director in Cylab Biometrics Center at Carnegie Mellon University (CMU). His research interests focus on various topics, including Biometrics, Face Recognition, Tracking, Human Behavior Understanding, Segmentation, Scene Understanding, Domain Adaptation. He has received four patents and two best paper awards and coauthored 100+ papers in conferences, technical reports, and journals. He was a vice-chair of Montreal Chapter IEEE SMCS in Canada. He is a co-organizer and a chair of CVPR Precognition Workshop in 2019, 2020, 2021; MICCAI Workshop in 2019, 2020 and ICCV Workshop in 2021. He is a PC member of AAAI, ICPRAI in 2020 and 2021.

Dr. Ashley Dowling is a Professor in the Department of Entomology and Plant Pathology at the University of Arkansas in Fayetteville, USA. His lab will provide expertise in insect biodiversity and identification. He will also participate in the intellectual development and training of the artificial intelligence system and design of the data collection system. Dr. Dowling's lab focuses on identification, ecology, and evolution of insects living in both terrestrial and aquatic habitats and has 70+ papers on arthropods. Dr. Dowling and his lab will conduct insect capturing, handling, and identification, which is critical for successfully training the computer to identify a diversity of insects. Dr. Dowling also has extensive experience imaging insects, both alive and dead, and will help develop the image capture system on the trap and assist with the integration of these components into field-ready traps.

Introduction

The short-term goal of this project is to create and evaluate a model's performance with our current progress in imaging and labeling to verify the proof of concept of our long-term goals; this is the primary focus of this paper. The long-term goal of this project is to develop a novel AI-based technology to monitor species of insects and provide real-time agricultural recommendations to farmers. A smart machine that utilizes this AI technology would give farmers as well as crop surveyors access to a continuous flow of data and information; a prototype of this design is shown in Figure 1. The final product incorporating the research shared in this paper would be a similar machine to the one shown; it could calculate when to apply the necessary chemicals and pesticides, the proper dosages, and timing of application, likely catching outbreaks before they occur and reducing overall pesticide use while also providing information to the agricultural community to make informed decisions regarding insect management. All of which will save the US farm industry money and, through the reduction of pesticides entering the environment, ultimately, make the world a much safer place. The proposed solution stands to have an enormous impact on both the economy and environment.

The work in our lab is focused on creating an automated system that can detect and identify arthropod specimens. In order to identify each insect that these AI systems encounter, a model must be trained first. This work requires the imaging of tens of thousands of insects; these images will then be used to train an AI for later work. In order to verify the accuracy of the system, it will be tested on novel data gathered in the same locality of the existing insect dataset. Eventually, this work will be optimized for low-power deep learning in order to deploy it on low-cost devices. The final primary goal of the project is to submit and publish multiple papers for top AI conferences and journals. Right now, we are working on a funded project to develop a prototype system that can detect and capture photos of insects; this work will be used to develop the previously mentioned AI that can classify insect species. At the current stage of research, we have captured around 7,000 images but have labeled less than 5% percent of these images: examples of labeled images can be seen in Figure 3. The rate at which it takes to label these images inhibits the production of a model that can reliably identify images, as the model greatly benefits from being able to classify each part an image. The process of labeling an image requires carefully tracing the outline of each body part: this list includes the body, head, legs, and wings.

Figure 1: Testing a prototype of our developed AI-based insect detection and counting system.

By labeling each part of the insect, the model can distinguish between different species, increasing the reliability of properly identifying any given insect. In order for a human to classify an insect, one must inspect each part of the body, with the wings being the most important. If a human, or a computer model, knows what to look for in the wings of the insect, the chances that the insect is correctly identified greatly improves. The process of identifying each pixel in an image is referred to as semantic segmentation in computer vision, and annotation refers to the manual process of semantically identifying each part of an image.

Automatic semantic object understanding and segmentation are computer vision and machine intelligence operations that aim to assign each pixel in an image to a corresponding, predefined class; this data is then used to train AI models. Semantic segmentation has various practical applications such as medicine, agriculture, law enforcement, and transportation. When a model is needed to recognize details and structures of objects, semantic segmentation is a reliable approach. A typical supervised segmentation model is trained on datasets with labels. To train an AI to semantically segment images, a few learning approaches can be used, but all approaches require a sizeable dataset, and the more dependable ones require annotation. However, manually annotating insect images for the semantic segmentation task is costly and time-consuming. For example, our current progress of manual segmentation and annotation is not sustainable, as the time it takes to annotate an image (as shown in Figure 2) vastly outweighs the time it takes to capture an image. Selecting the right machine learning approach can help to alleviate this problem.

The three primary machine learning approaches are supervised, unsupervised, and semi-supervised learning. Supervised learning uses data that has already been labeled, and the model learns from this data, but this approach requires a large amount of labeled data. Unsupervised learning allows the AI to recognize patterns on its own without the aid of labeling, but the results are usually not as accurate when compared to supervised methods. Semi-supervised learning is a combination of both: the model learns on labeled data then uses the unlabeled data for further training. Domain Adaptation offers a solution to the problem of labeling while also maximizing model accuracy; it uses simulated data to train a model used for real-world applications. The simulated data, including ground truth labels, is used to train the model. A ground truth label refers to the annotated image used as the baseline for training. Once the model is trained, the knowledge is transferred and applied to the real-world data. This approach allows the model to use large amounts of labeled data, but there is usually a slight difference between the simulated data and the real data, referred to as the domain gap. This domain gap is then minimized by training the model on the unlabeled real-world data. Richter *et al* [13] pioneered one of the more well-known applications of Domain Adaptation by using information from the game GTA V provided by the game engine to create a new, virtual dataset. The model's knowledge is usually transferred and refined on real-world city images, discussed further in papers such as AdvEnt. The ability to maximize the efficiency of a model using the methods found in the AdvEnt paper[10] does not only apply to scenarios which require simulated and real-world data: any dataset of labeled and unlabeled images that requires generalization across a domain gap can benefits from Domain Adaptation. By treating the labeled insects as the simulated data and the unlabeled insects as the real-world data, we were able to produce a model that can segment images of unlabeled insects.

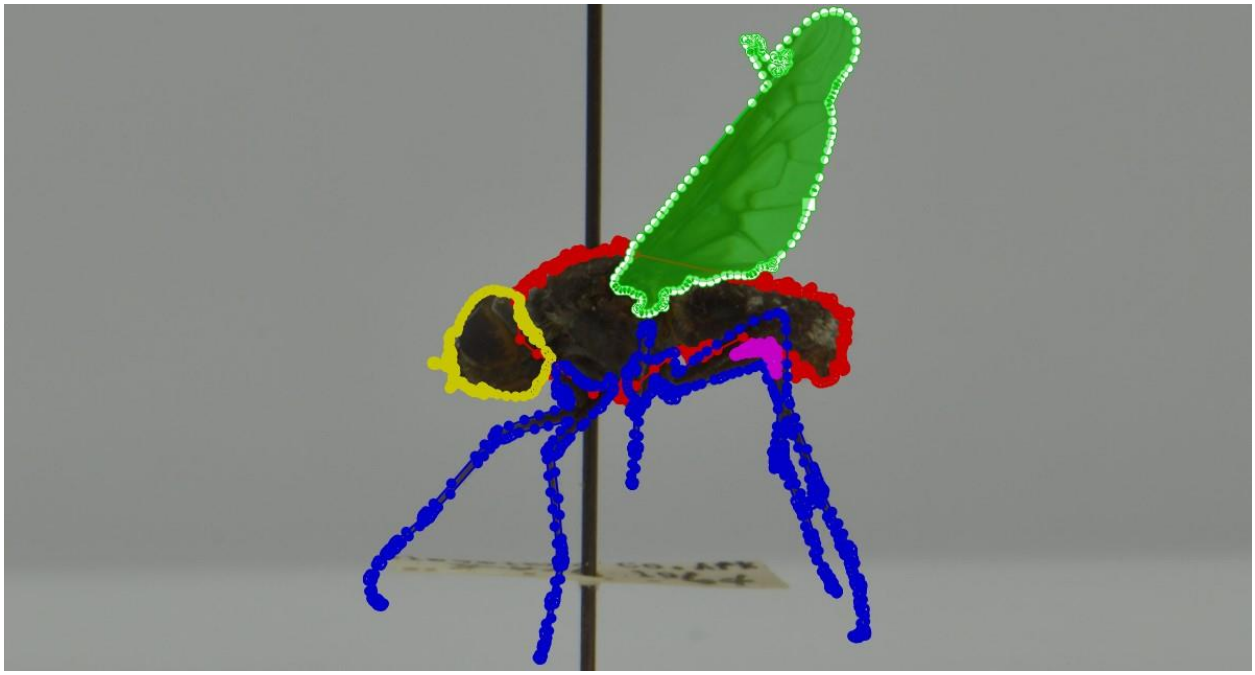

Figure 2: An example of an annotated image. Labeling an image requires tracing an outline around each part of the insect.

Related Work

Unsupervised Domain Adaptation has recently seen a rise in popularity, prompting more research activity, and when it comes to semantic segmentation, many of the common approaches use generative adversarial training. Adversarial Networks focus on training a generator and discriminator. The generator creates results that mirror the training data, while the discriminator identifies the results that do not fit the training data. Together, the two continue improving results until the generator can create images, that either reach the desired output or convince the discriminator that they are authentic images. Work in our lab related to semantic segmentation implements a Bijective Maximum Likelihood loss to improve the results of scene segmentation. Truong *et al* [9] also used a Domain Score to measure the efficiency of a model on a new domain. The first GAN approach applied to domain adapted semantic segmentation was used by Hoffman *et al* [4]. Yang and Soatto improved their segmentation results by performing domain alignment to reduce the variance between the source and target domains. Cheng *et al* [2] implemented a dual path learning framework that allows two pipelines to interact and improve segmentation results. Ning *et al* [6] used a multi-anchor approach resulting in more representative labels in the target domain, as opposed to traditional centroid based UDA methods.

Insect detection and other agricultural applications of computer vision have been researched in the past. Insect detection in nature relies on small object detection and sufficient generalization, ensuring the methods can work in complex environments. Deng *et al* [3] focuses on using a biologically inspired detection method to identify insects. Kuzuhara *et al* [5] utilizes a two-stage method based on CNNs for detecting and identifying small insects. Research done by Rani uses computer vision techniques to determine whether agricultural crops are affected by pests by using an SVM classifier [5]. Wang *et al* [11] uses an Artificial Neural Network and a Support Vector Machine to improve accuracy results in identification. Chen *et al* [1] created an inexpensive system that uses various acoustic and optical sensors

to classify insects. The research done by Samata and Ghosh uses correlation-based feature selection and incremental back propagation in an artificial neural network to detect insects and reduce their impact on crop production.

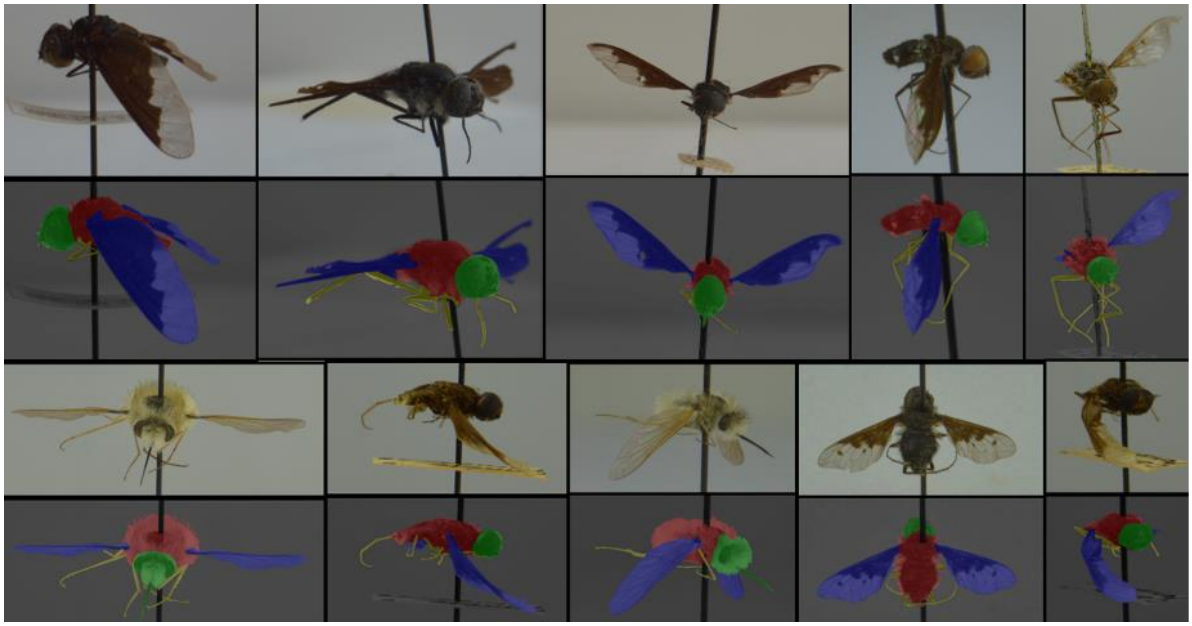

Figure 3: A dataset (7,000 samples) of captured insect photos and their detailed annotation used during training. Part of the research included collecting and labeling some of these samples.

Methods

Creating a model that can attain the intended results is approachable in a few different ways. The first of these methods uses unsupervised training. At first glance, unsupervised learning may seem like the best approach for our problem: we have an abundance of unlabeled data that would take a significant amount of time to label. However, unsupervised learning has its limitations. The main concern is the risk of inaccurate results. Training a model to segment images is difficult enough, and segmenting small images is even more challenging. Expecting an unsupervised model to reach the desired results is more than hopeful. Validating the results is another concern with unsupervised methods. In order to improve the accuracy of unsupervised learning, human input is often required to ensure the model is approaching the problem correctly. The process of verifying the output of an unsupervised model requires a significant investment of time. Additionally, unsupervised methods usually require larger training sets, which can increase the computational complexity of the system. This also results in lengthier training times, slowing down the pace of improving the results. Overall, unsupervised training is a gamble when it comes to the intended outcome.

Supervised training, on the other hand, requires large amounts of labeled data. Currently, labeling an insect photograph takes around 15 minutes. Labeling the entire dataset of photographed arthropods would take a tremendous amount of time. The room for human error also increases with supervised learning. Improperly labeled images can skew the training results and cause problems for the model's accuracy. For more complex problems, the images may also need to be labeled by an expert in the field in order to properly identify each part of the image. Another problem with supervised training presents

itself when the model is applied to the target domain. Usually, the model performs very well on the source domain, but supervised methods can have problems generalizing if the dataset does not include a wide variety of images. Training a supervised model can also take considerably more time than other methods, as each image and its corresponding label needs to be analyzed. Overall, supervised training usually produces better results as opposed to unsupervised methods, but the time and resources required to achieve these results can be inhibiting.

The semi-supervised method we used combines the benefits of the two styles of training while also maximizing the accuracy of the model. Semi-supervised methods train the model by using both labeled and unlabeled data. In the case of our research, a generative model was used. The training data provides ground truth labels and a baseline for the intended results. The unlabeled data allows the generator to learn how to segment the images while the discriminator continues improving the results. The semi-supervised method of training reduces the time it takes to train as well as the overall complexity of the model. Additionally, the amount of labeled data required does not compare to the supervised method, and the results are better than those of an unsupervised method. No human input is required to verify the results, either. A figure of the model is displayed below (Figure 4).

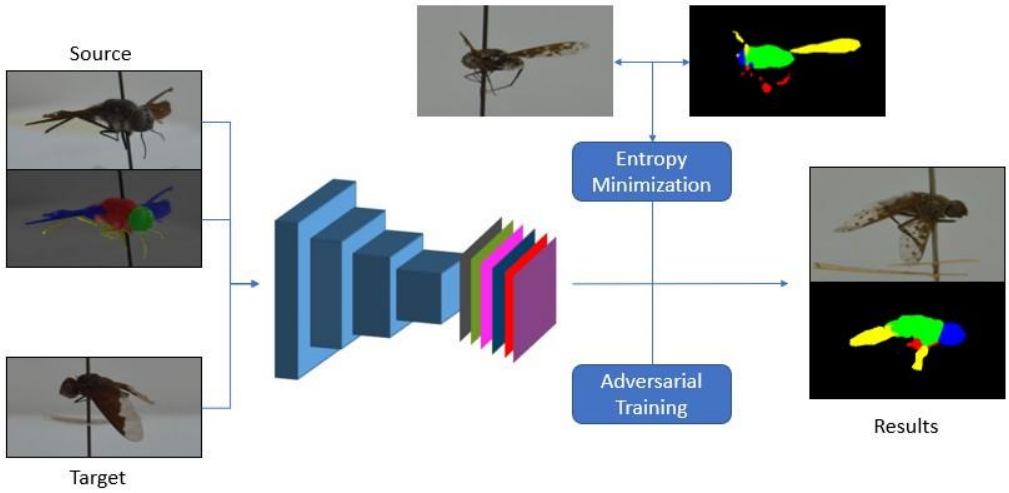

Figure 4: Graphical indication of the methods used to train the model: Domain Adaptation and Adversarial Training.

Results

The DeepLabv2 model was used during training along with the AdvEnt domain adaptation methods. In order to run the experiment, the AdvEnt datasets needed to be modified. First, the insect label files were converted to the ground truth masks and moved into a repository along with the image files. Each class needed to be changed, too. At this point, the network was being used to segment insect body parts rather than city scenes. Once these steps were completed, the model was trained on the ground truth labels.

The unsegmented images were used during training to allow the model to holistically learn the structure of insects and the segmentation patterns. After the model was sufficiently trained, it produced several

segmented images on the unlabeled data. The mean IoU achieved by the model was 38%. IoU, or intersection over union, refers to an algorithm that identifies the overlap and union between the ground truth label and the output produced by the model. The intersection of these two parts is divided by their union to produce the IoU value. Based on this value, one can evaluate the model's efficacy. An IoU value greater than 50% is considered good: because these are preliminary tests, the final number we achieved is promising. The final results of our experiments can be seen in Figure 5.

Conclusions

One thing to note was the model's high accuracy when segmenting the side profile of insects and the accuracy in segmenting the head; the wings and body are not as accurate. The model cannot segment legs.

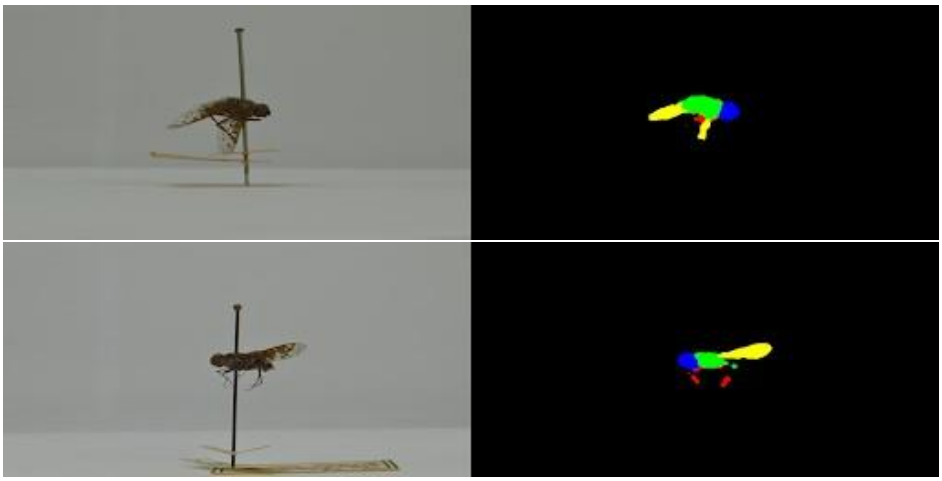

Figure 5: Segmented images produced by the model after training.

However, small objects cannot be reliably segmented by most models. Additionally, the model does not generalize well: insects with different sizes or colors cause issues. From the images, we can learn how to improve the results of the model. Including more variety in the insects used to train the model would allow it to segment different insect types more reliably. Incorporating other methods that segment small objects reliably and improve overall accuracy would likely improve results, as well.

Acknowledgements

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Fine Roman Dining at Affordable Pompeian Prices: Reevaluating the Commercial Gardens of Pompeii

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Abstract

Previous scholarship has designated Roman gardens into binary *otium* or *negotium* designations; however, this research on Roman gardens suggests that these concepts often exist in spaces simultaneously. The reevaluation of commercial gardens in Pompeii presented in this article allows for an integrative analysis of garden spaces, which reveals that commercial gardens have coinciding qualities and functions with private elite gardens and that various trades were actively integrating these features into commercial settings to promote and financially supplement their businesses. This research challenges the assumption that non-domestic, commercial gardens only have qualities indicative of *negotium* and that garden spaces were not multifunctional. My research reflects that these gardens were combining elements of *otium* and *negotium*. This evidence suggests non-elite Romans used non-domestic, commercial gardens for pleasure just as elite members of society did in their own private gardens or simulated garden rooms. My work highlights that a new, inclusive, and multifunctional approach to commercial gardens is needed in order to consider the role they had in shaping the urban experiences of the non-elite class during the early Roman Empire. This reevaluation contributes to a more holistic understanding of the urban experience in Roman society by focusing on how the businesses used and democratized commercial gardens in Pompeii during the 1st c CE.

Keywords: Pompeii, Commercial Gardens, *Otium*, *Negotium*, *Triclinium*

Profiles of the Authors

Claire Campbell received her BA in Classical Studies with a minor in Jewish studies at the University of Arkansas in Spring 2021. She currently working towards her master's degree at Yale Divinity School, focusing on Hebrew Bible and Second Temple Period Judaism. This manuscript is revised from a chapter of her undergraduate honors thesis on the analysis of non-domestic garden spaces in Pompeii. She is continuing to incorporate this research into her study of ancient agriculture and economics as reflected in the literary and material evidence during the Second Temple period in the Ancient Mediterranean and Ancient Near East.

Dr. Rhodora G. Vennarucci received a BA in Classical Archaeology at the University of Michigan and an MA and PhD in Roman Archaeology from the University at Buffalo, SUNY. She is currently an Assistant Professor of Classics at the University of Arkansas, where she teaches on a variety of topics, including Greek and Roman art and archaeology, Roman urbanism, virtual archaeology, and Latin epigraphy, and leads study abroad programs to Italy. She received the Fulbright College Master Teaching award in 2021. Her research focuses on the socio-economic history of the Roman world with published and forthcoming works investigating both ends of the distributive system in Italy: rural multi-craft production and urban commercial landscapes. She co-directs the Marzuolo Archaeological Project in Southern Tuscany and the Virtual Pompeii Project. Her most recent project, Virtual Roman Retail, uses immersive VR technology as a multisensory tool for exploring consumer experience and behavior in Roman shops.

Introduction

"Non arboribus consita Italia, ut tota pomarium videatur?" "Isn't Italy covered with trees that the whole land seems to be an orchard?" (Varro *Rerum Rusticarum*, 1.2.6). The Italian peninsula was remarkably prosperous during the Roman empire; even the environment reflected the wealth of Rome through luscious verdure. Gardens were a means of expression in the ancient world, just as they are today. The literary and art historical evidence depict famous gardens owned by influential political figures in Rome. However, these "physical remains" of ancient gardens are limited to the authors and artists who portrayed them in their works. While these types of evidence of significant for research in Roman gardens, the result is that scholars have tended only to study Roman gardens associated with elite society. Roman garden scholarship has not yet systematically analyzed gardens connected to commercial settings. Previous scholarship has encouraged an approach to the study of Roman urban horticulture by placing the gardens in binary categories, such as pleasure or productivity (Grimal, 1969). Recent scholarship has shown that these categories are not always static. However, the focus in scholarship remains on private gardens like those found in the peristyles of elite houses and villas, thus perpetuating the identification of *otium* (leisure) with the lives of the elite (Simelius, 2018; Wickham, 2012).

The unique preservation of Pompeii by Mount Vesuvius in 79 CE provides us with the material evidence of horticulture development and practices during early Rome Empire, making this site invaluable to Roman garden scholarship. After reviewing the archaeological evidence found in the market-gardens in Regio I of Pompeii, it became evident to me that features associated with elite society were also incorporated into cultivated commercial gardens. Because there is no clear consensus in scholarship as to what constitutes a commercial garden, I have defined it as a garden linked to a business whose facilities would have been accessible to the public for a price. The resulting reevaluation of commercial gardens in Pompeii challenges the assumption that Roman gardens were only used for *otium* or *negotium* (work).

I primarily analyzed evidence pulled from the work of W. Jashemski, who pioneered research on Roman gardens through the excavation and analysis of the preserved gardens found in Pompeii (Jashemski, 1979, 1993). Volume two of her work compiled all identified gardens in Pompeii and organized them by region, *insula* (city block), and entrance number. She provided the excavation history, art and architectural evidence, and palaeobotanical evidence for each garden. My research has focused primarily on the commercial garden spaces in Regio I and Regio VI that have archaeological evidence of masonry *triclinia* (a three-sided couch, used for reclining and eating; also used to describe dining rooms) (Fig. I). I analyzed the archaeological evidence of nine commercial gardens from Regio I and Regio VI. I then organized these gardens into five categories: *taberna* (tavern), *caupona* (restaurant), *hospitium* (inn), *lupanar* (brothel), and market-garden. These terms have encouraged monofunctional interpretations where the archaeological record indicates a commercial space was multifunctional (Ellis, 2018, p. 25). These terms are often applied to Pompeiian structures by modern excavators uncritically. For the purpose of this research, I have retained these labels to maintain structure in this reevaluation. Owners of commercial premises in Pompeii marketed *otium* by integrating dining facilities within cultivated garden spaces. I believe they were doing this to promote their business among the general public and thus increase potential revenue.

Figure I: Masonry triclinium from the Inn of the Gladiator, Pompeii (pompeiinpictures.com).

Survey of Commercial Gardens

Market-Oriented Gardens in Regio 1

Market-gardens have been identified in traditional scholarship as gardens with the sole function of the cultivating of produce to sell (Jashemski 1973).

The Orchard of Felix (1.22): This large orchard has been associated with the fruit-seller Felix, whose *taberna* was only four blocks north of the orchard on the *Via dell'Abbondanza,* the busiest thoroughfare in Pompeii (I.8.1-2) (Bergmann, 2018, p. 291). The orchard is approximately 1,852 square meters in size. Jashemski only excavated half the plot, but she concluded the garden may have maintained 300 trees. The palaeobotanical analysis and the complex irrigation system found in this site suggest most of these were fruit trees. This garden has evidence of a masonry *triclinium*, altar, and a decorated table with an ornate marble plaque. The *triclinium* was placed beneath large olive trees to take advantage of the shade (Jashemski, 1993, p. 73).

The Garden of the Fugitives (I.21.6): This market-garden was connected to a *caupona* (I.21.2). The garden is approximately 1,872 square meters. There is evidence of a large masonry *triclinium* and a pergola in the middle of the garden positioned closer to the west wall. There is a base near the *triclinium,* on which would have been placed a table or a statue. The condition of the garden did not permit an extensive palaeobotanical excavation, but the evidence indicates the garden may have maintained trees. (Fig. II). Around the *triclinium* were large vines, which likely covered the pergola. Because the garden included fruit trees, vines, and decorative shrubbery, Jashemski referred to it as "mixed cultivated" (Jashemski, 1993, p. 69-70).

Figure II: Market-garden and triclinium *foundation in the Garden of the Fugitives, Pompeii (PIP).*

Inn of the Gladiator (I.20.1): This market-garden, also connected to a *caupona*, has a plot about 1,213 square meters in size. Jashemski believed this garden once held a vineyard, although the garden was poorly preserved (Jashemski, 1993, p. 67). There is also evidence that some trees, likely fruit trees, were grown on this site. The multiple *dolia* (storage vessels) and the pressing room discovered in the garden indicate wine may have been made as well as served here. In the east part of the garden, excavators found an altar behind the pressing room. Frescoes were in the garden, but they were not well preserved. There is evidence of a table and *triclinium*. Near the *triclinium* was placed a statue of a gladiator (Fig. III). It has been suggested that the two decorative pools behind the *triclinium* may have held eels or fish (Jashemski, 1993, p. 67).

Figure III: Vineyard with statue of gladiator and dolia *in the Inn of the Gladiator, Pompeii (PIP).*

It seems likely that the market-gardens, the largest gardens in Regio I of Pompeii, had supplied produce to the shops and businesses to which they were associated. However, unaddressed by scholars is the choice to incorporate dining facilities into market-gardens. Why did they build these dining facilities? This decision certainly did not improve or enhance the production of fruit in these spaces. Perhaps the proprietors

used these facilities themselves, but the *triclinium* found in the orchard possibly associated with the shopkeeper Felix (I.22) appears too grand for the sole use of a shopkeeper and his family (Jashemski, 1979, p. 411). It seems reasonable to suggest these dining spaces were rented out to customers, who did not have their own gardens or dining spaces at home; as well as visitors to Pompeii, such as those who came to town for the gladiatorial spectacles in the nearby amphitheater. I would suggest that proprietors of the other large market-gardens also made their dining facilities accessible to customers for a price.

Perhaps the owners of the market-gardens used the aesthetic value of productive plants and garden dining to promote and financially supplement their business. The palaeobotanical evidence confirms these market-gardens had grown the same fruit trees identified in garden frescoes decorating elite spaces. This evidence emphasizes the elite association between gardens and dining activities. (Kellum, 1994; Caneva, 2003; Bergmann, 2018). Instead of a simulated reality produced by high-status garden décor in exclusive elite dining rooms, the market-gardens offered customers the opportunity to dine in semi-seclusion in an actual orchard that would have been the original inspiration for the elites' simulated gardens. Businesses willingly incorporated *triclinia* that decreased the space for cultivation in the garden; the likely tradeoff was that these dining facilities increased potential revenue and consumer traffic. The introduction of large ornate *triclinia* in the middle of cultivated spaces was a measured response to customers' desire to dine in gardens.

Gardens in Cauponae *in Regio 1 and Regio VI*

A *caupona* was a business that provided food and sleeping accommodations (Ellis, 2018, p. 26).

Caupona I.13.16: The *caupona* at I.13.16 has evidence of a *triclinium* under a shaded structure as opposed to being in the middle of the garden space, as was the case in the market-gardens discussed above. The structure was built into the northwest corner of the garden (Fig. IV). The garden is approximately 88 square meters. Jashemski identified this garden as a small-scale vineyard (Jashemski, 1993, p. 58). The cistern head in the middle of *triclinium* served as a table base. The walls of the *triclinium* were decorated in fresco with portraits of the goddess Venus, the patron of Pompeii; and the god Priapus, the patron of commerce and protector of fortunes. Both figures were recognizable across society, but perhaps the owner revered these gods and wanted them expressed in the decoration.

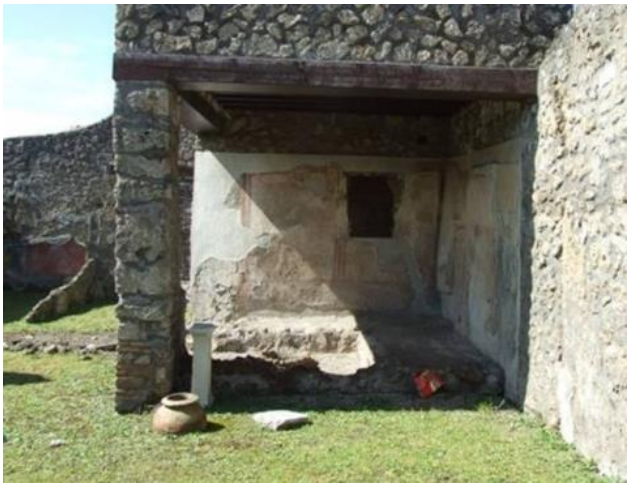

Figure IV: Shaded masonry triclinium *in I.13.16, Pompeii (PIP).*

Caupona VI.1.1: The garden associated with this *caupona* is only 53 square meters in size. There is evidence of a *triclinium* and a pergola. The *triclinium* takes up most of the space in the northeast corner. There are no altars or decorations, but there are a gutter and a cistern, which indicate the potential for cultivation (Jashemski, 1993, p. 119).

Caupona VI.2.3-5: This *caupona* has three garden spaces. The large garden is approximately 91 square meters; the intermediate garden is 50.5 square meters; the small garden is 35.5 square meters (Fig. V). A *triclinium* and a pergola were built into the northern portion of the large garden. In the middle of the *triclinium* was placed a small pool and table base. Excavators discovered a masonry altar with no decorative elements in front of the *triclinium.* The two smaller gardens in this *caupona* have no evidence of dining or worship (Jashemski, 1993, p. 121). None of the gardens have any palaeobotanical evidence, but the access to water resources through gutters and cisterns suggests that these gardens may have provided the *caupona* with small produce, such as herbs and vegetables.

Figure V: Plan of VI.2.5-3, Pompeii (PIP).

The gardens inside these *cauponae* are smaller than the market-gardens attached to the *cauponae* analyzed above. However, the *cauponae* integrated the garden dining experience into their business despite not having access to a large garden space. By installing *triclinia* in innovative ways, business owners provided the elite experience and also maintained the productive potential of the garden. The *caupona* I.13.16 shows a unique *triclinium* that was built into the side of the garden wall. If the *triclinium* had been placed in the middle of the garden, it would have occupied much of the 88 square meters. This installation would all but eliminate the cultivation of produce. Therefore the business strategically placed the structure to the side. Market-gardens were large enough for owners to incorporate dining structures in the middle of the spaces. Businesses with much smaller gardens had to think of innovative ways to include *otium* into their available space and still maintain adequate room for the cultivation of their crops.

A similar type of shaded dining structure is seen in the literary and art historical evidence of Rome. Pliny the Younger described a marble pergola to the side of his garden with large open walls or windows that permitted a full view of the garden and yet protected him and his guests from the elements (Pliny the Younger, *Epistulae*, 5.6.39). The frescoes of the House of the Fruit Orchards (1.9.5-7), a private residence in Pompeii, also depicted pergola structures into the frescoes to make the viewers feel as if they were looking out onto a garden through a pergola. These shaded structures would provide a relaxed and comfortable garden dining experience in a hot Mediterranean climate (Fig. VI).

Figure VI: Fresco from the House of the Fruit Orchards, Pompeii (PIP).

The *cauponae* of Regio VI did not build the *triclinia* under shaded structures; however, the position of the *triclinia* would suggest that businesses with smaller gardens willingly sacrificed cultivation space to provide the garden dining experience to their customers. The *triclinium* in VI.2.3-5 separates two gardens at the east and the north side of the establishment, decreasing the potential for cultivation. The *triclinium* and pergola in VI.1.1 occupy more than half of the 53 square meters of garden space, leaving very little open green space for plant life. The restricted garden spaces would only allow for smaller trees, shrubbery, or flora to be maintained. It would again seem that businesses were choosing to provide dining facilities in their gardens even if they decreased the garden spaces. Presumably, the revenue potential that garden dining had for these business owners more than made up for the loss of income that owners would have received from additional crops.

Hospitia *in Regio I and Regio VI*

Hospitia, also associated with lodging and sometimes dining, were smaller establishments than *cauponae* (Ellis, 2018, p. 30-34). Regio I has three gardens with *triclinia* associated with *hospitia*. Smaller businesses do not have access to large garden spaces like the Orchard of Felix (I.22), but the gardens have enough space to prioritize activities such as dining. *Triclinia* found in these commercial settings take up most of the green spaces. This evidence would suggest that business owners considered it more important to provide an outdoor dining venue than to maintain a full garden. As noted earlier, this was also true of the *cauponae* gardens of Regio VI.

Hospitium of Saturninus (I.11.16): The *Hospitium* of Saturninus did not have a physical garden space but does have evidence of a simulated garden room inside the establishment. The faux garden room was not common in commercial settings and has been primarily associated with elite society. Therefore, this evidence offers a unique opportunity to analyze the rationale of the investment of the garden-inspired fresco in relationship to the business.

The *triclinium* in the courtyard at the rear of the *hospitium* had garden frescoes on the north and east walls (Fig. VII). The poor preservation of the fresco does not allow for the plant and wildlife to be identified. It appears to depict a dense garden with minimal decorative elements (Fig. VII) (Jashemski, 1993, p. 53, 325). Although a garden fresco would not permit customers to dine in a garden, the painting would not require the maintenance that a physical garden would and was therefore even more strongly associated with *otium*.

Figure VII: Fresco from the Hospitium *of Saturninus* triclinium *(PIP).*

The *Hospitium* of Saturninus invested in the outfitting of a garden room inside the inn, emulating a real garden experience with simulated images of flora and fauna that guests could admire while dining inside. Private residences would have access to private gardens but were also able to expand their gardens through decoration inside the house. Businesses were practicing this as well, also seen in the garden rooms in the *lupanar* I.11.10-11 examined below. The owner of this *hospitium* had invested in his business by providing an enhanced elite experience in a faux garden room, similar to the style of the simulated garden room found in the Villa of Livia (Prima Porta, 1st c BCE). This famous garden room provided the Imperial family with a garden dining experience inside their villa (Fig. VIII). The garden room is an early example of the garden fresco style and is considered a coveted elite trend during the early empire. Based on the evidence in Pompeii, private and public settings also invested in this style by the 1st c CE, supporting the idea that the relationship between the garden and dining was a significant concept in Roman society.

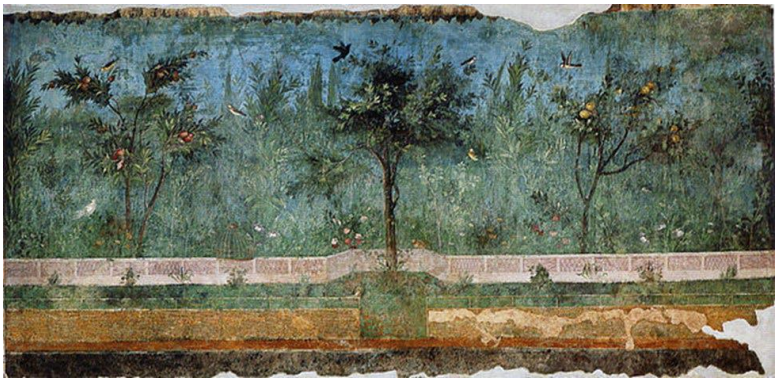

Figure VIII: Fresco from the Villa of Livia, Prima Porta (1st c BCE) (milestonerome.com).

Gardens in Lupanaria *in Regio I and Regio VI*

Lupanaria were brothels, but they were also associated with the retail of food and drink (Ellis, 2018, p. 7).

Lupanar of Euxinus and Iustus (I.11.10-11): The size of this garden is approximately 270 square meters. Jashemski identified this establishment as a *lupanar* (Jashemski, 1979, p. 175). Two small structures that open out towards the garden were built onto the south and east walls (Fig. IX).

Figure IX: Shaded triclinium structure from I.10.11 (PIP).

These rooms likely served as *triclinia*, where guests could eat in the shade and enjoy the view of the garden. The walls of the rooms have evidence of frescoes that depict a small fence with plants behind it. This establishment invested in garden-inspired frescoes painted onto structures already built in the garden, enhancing the experience of *otium* for customers. The frescoes are too poorly preserved to determine if they are in the same style found in the *Hospitium* of Saturninus and the Villa of Livia. The palaeobotanical evidence suggests that the garden maintained grapevines. The *dolia* found on this site may have been used to make and store wine (Jashemski, 1993, p. 51).

Lupanar of Aphrodite, Secunda, Nymphe, Spendusa, Veneria, Restituta, Timele (VI.11.5, 15-16): This establishment has been identified as a *lupanar* based on erotic graffiti that lists prices for certain services (McGinn, 2004, p. 275). The garden is approximately 201 square meters in size. There is evidence of a masonry *triclinium* in the northwest corner of the garden (Jashemski, 1993, p. 143). There is no palaeobotanical evidence to indicate the type of plants grown in this garden, but the size would have allowed a decent-sized garden to grow vines, fruit trees, flora, etc.

The *lupanaria* in Pompeii are far from luxurious; rather, they are often dingy and cramped. The gardens provided a spacious aesthetic environment for customers to dine and relax. A *lupanar* may not seem very appealing to customers from the inside, but the access to a flourishing garden where one could dine with other customers and prostitutes would have made the business more appealing.

There is also evidence that prostitutes took strategic advantage of gardens in Rome during the 1st c BCE. The gardens in the portico of Pompey the Great were accessible to the public. They also reflected the success and extent of the Roman Empire through the presence of exotic plants and trees. Famously, the gardens were also the haunt of local prostitutes (McGinn, 2004, p. 153). Prostitutes would use the sensual setting to attract customers, just as the gardens in the brothels at Pompeii would have brought a competitive edge to the business. A *lupanar* with a large garden would entice customers to return for the elite experience in a setting that was not usually considered *otium.*

These *lupanaria* incorporate different types of structures used for dining. The brothel at I.11.10-11 provided garden rooms, similar to the shaded structure seen in the garden of *caupona* I.13.16. Although scholars debate the extent of prostitution practiced in *cauponae*, it is likely that women, enslaved and freed, would have served and entertained the guests dining in the gardens (Laurence, 1994, p. 79). Perhaps the prostitutes in these *lupanaria* dined with and entertained customers in the gardens for an extra cost. In addition to their primary commercial function, these brothels may have used the gardens to cultivate produce, making these commercial gardens multi-functional.

Conclusion

Dining in gardens has been traditionally considered an exclusive luxurious experience and has not often been viewed as accessible or even affordable to most members of Roman society. My research on Pompeii commercial gardens suggests that gardens were accessible and enjoyed across the socioeconomic spectrum. The construction of public gardens attested at Rome starting in the late republic and continuing under Augustus helped democratize garden access to a larger part of the population in and outside of Rome. Large gardens in crowded urban settings would also have been beneficial to the environment. The commercial gardens in Pompeii could have offered benefits beyond the value of their produce, such as shade, space to relax and socialize, decrease in noise and air pollution, and other aesthetic qualities. Ancient authors also believed urban gardens were valuable for improving the health of local inhabitants (Vitruvius *De Architectura,* 4.9.5). We can see this trend in our own urban settings. Cities and neighborhoods intentionally incorporate green spaces into their landscape that benefit the residents and the environment (Wolf, 2017). My research argues that this shift was also visible in the commercial gardens of Pompeii.

Based on my analysis of the commercial gardens in Regio I and Regio VI of Pompeii, the evidence indicates various trades may have been marketing *otium* through their gardens to benefit their business. This new insight forces a reconsideration of public accessibility to elite experiences. The accessibility of public garden spaces to the general populace reflects a trend of inclusiveness in Roman retail that challenges the central elite focus in Roman garden scholarship. This reevaluation of commercial gardens in Pompeii suggests that establishments involved in the service industry had a significant role in democratizing garden access to a larger part of the population by the early Imperial period. As more of the population participated in what had previously been exclusive elite activities, the concept of *otium* in the garden was commodified and more broadly became a part of the Roman urban experience. With this new insight in mind, we can start to consider what social and cultural meaning dining in the garden may have had for the non-elite customers willing to pay for the experience.

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Increasing Student Comfort with Addressing Microaggressions: Ouch! That Stereotype Hurts

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Abstract

Students on college campuses are not prepared or equipped to defend themselves or their peers when they experience or witness a microaggression. The purpose of this study was to measure the impact of the Ouch! That Stereotype Hurts program on student comfort level when addressing microaggressions and other gender, racial and cultural insults. This educational program provides examples of different types of microaggressions seen in classrooms and workplace scenarios. The program is a 30-minute individual, self-paced, guided eLearning program that enables learners to explore communication skills for promoting inclusion and respect among their peers. Participants were 91 undergraduate students (primarily White women) attending a mid-south university enrolled in a 3-hour online general elective course in Fall 2020 or Spring 2021. Students completed a pre-assessment in the 5th week of classes, and the Ouch! 30-minute training program and post-assessment the following week. On average, students' knowledge did not change; however, students' comfort level did increase significantly: On average, 50% of students reported feeling comfortable addressing microaggressions, which increased to 95% of students after completing the 30-minute Ouch! program. The present study's participants were primarily White students living in the mid-south. This research indicates that students, especially those who identify as White, would benefit in their comfort level when exposed to diversity educational training on a college campus. Keywords: stereotypes, microaggressions, training, higher education.

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Devin Boggs Riley is a recent graduate (BS) of Human Development and Family Sciences in the School of Human Environmental Sciences in the Dale Bumpers College of Agricultural, Food and Life Sciences at the University of Arkansas. His research examines the harmful effects of stereotypes and microaggression on faculty and students in higher education learning. He currently works in the College of Education and Health Professions in curriculum and instruction for the EMPOWER program. His focus is on creating functional academics for students with intellectual disabilities within post-secondary education.

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Bryan Hill earned a B.S. and M.S. in Industrial Engineering and a Ph.D. in Public Policy from the University of Arkansas. Currently, Bryan is the Associate Dean for Student Success in the College of Engineering.

Introduction

Students on college campuses are not prepared or equipped to defend themselves or their peers when they experience or witness a microaggression. The purpose of this study was to measure the impact of the *Ouch! That Stereotype Hurts* program on student comfort level when addressing microaggressions and other gender, racial and cultural insults. This program educates and gives examples of different types of microaggressions seen in classrooms and workplace scenarios. In total, *Ouch!* is a 30-minute individual, self-paced, guided eLearning program that enables learners to explore communication skills for promoting inclusion and respect among their peers.

One of the challenges for high impact learning in higher education is the shifting demographics and increased diversity in the communities of the United States, which can challenge administrators, faculty and students to be more knowledgeable and responsive to their diverse communities. The student population is increasing in terms of race/ethnicity, gender, and different SES backgrounds on university campuses (Locke & Trolian, 2018). The ideal higher education space is to have a diverse population and acceptance of all backgrounds. Unfortunately, higher education institutions are not faring well in race equality (D'Arcy & Galloway, 2018). Many students will experience the harmful impact of microaggressions during their time on college campuses. **"**Ouch moments" or brief exchanges are where an indignity, insult or slight is expressed, intentionally or not, from one person to another (especially towards a member of a minoritized or oppressed group) (Genhart, Garófoli Viviana, & Nadal, 2016). Research on microaggressions has grown exponentially (Wong et al., 2014), and schools and workplaces have sought ways to address them. Microaggressions were initially understood to describe discrimination towards African Americans (Nadal et al., 2014), however over the past several years, this research has extended to include other students of color, women, individuals with disabilities, ethnic and religious minority groups, and lesbian, gay, bisexual, transgender, queer or questioning (LGBTQ+) individuals (Nadal, 2011).

While there are many forms, race-related microaggressions increasingly impacts students' academic experiences. Racial microaggressions create race-related stress and can be described as the everyday, commonplace, and often ambiguous forms of racism faced by students of color (Grier-Reed, 2010). One study found that African American college students attending Primarily White Institutions (PWI) encountered a range of microaggressions in classroom settings and other campus settings by their white peers, faculty members, administration, and staff (Watkins et al., 2010). Yosso et al. (2009) discovered that Latina/o students experienced interpersonal and institutional microaggressions, as well as racial jokes. Microaggressions can be seen by some as harmless, but without correction, they can lead to dangerous actions towards minoritized groups. Thus, it is imperative that faculty, staff, and students on university campuses be educated on the effects microaggressions have on marginalized groups while also learning to feel comfortable and equipped to address microaggressive behaviors among their peers.

Unfortunately, individual barriers to responding to microaggressions include confusion, uncertainty and low comfort level. Byrd (2018) defines a "target" as an individual who experiences stereotypes or microaggressions; an "aggressor" refers to those who say or do something aimed at the target, and a "bystander" is someone who witnesses the situation. Targets and bystanders often feel confused and uncertain on how to respond to a microaggression (Ashburn-Nardo et al, 2008). It especially becomes difficult when microaggressions are typically said in a joking manner and seem unintentional, so targets and bystanders may be unsure on how to react. An effective response is confrontation, defined as verbal or non-verbal expressive displeasure with an aggressor's behavior (Focella et al., 2015). Confrontation effectively reduces the potential of future comments because aggressors are less likely to make biased remarks later (Czopp et al., 2006). However, confrontation is difficult for individuals who do not have the skills or resources to react in a situation.

The *Ouch! That Stereotype Hurts program* works alongside students and educators alike to provide a safe space for learning and growth while working towards dismantling microaggressions across campus and beyond. *Ouch!* started as a workshop in the mid-1990's and became a book and video-based training program ten years later. The program was created to address: "*Staying silent in the face of demeaning comments, stereotypes or bias allows attitudes and behaviors to thrive. This undermines the ability to create an inclusive environment where all are welcomed, treated with respect and able to do their best work. Yet, most who want to speak up don't know how. So, we say nothing."* This 30-minute training is an individual, self-paced, guided eLearning program offered online that enables learners to explore communication skills for speaking up when microaggressions occur in situations. The objectives are to help participants understand the impact of stereotypes and biased statements even when spoken casually, to identify the most common reasons people stay silent in the face of bias and other stereotypes, and to enhance skills for speaking up against stereotypes without blame or guilt (Aguilar, 2006). The current study was designed to measure the impact of the *Ouch! That Stereotype Hurts* p*rogram* with undergraduate students on a college campus.

Materials and Methods

Participants and Procedure

Participants were 91 undergraduate students (83% identified as women, 88% identified as white) attending a mid-south university, enrolled in a 3-hour online general elective diversity course in Fall 2020 or Spring 2021; the asynchronous courses were offered on the university's learning management system which students are already familiar with (i.e., Blackboard). Students completed a pre-assessment in the 5th week of classes, and then the *Ouch*! 30-minute training program and identical post-assessment the following week. All students were required to participate in the assessments and training as requirements for the course; IRB was deemed exempt by the primary institution of data collection.

Ouch! That Stereotype Hurts is a training program that includes multiple videos with vignettes and a final 10-question quiz. Our team used the identical 10 questions to survey students in the pre-assessment in the 5th week of classes; students were told that it was a survey and not a quiz and to provide their best guess (but were not being graded). These 10 items included definitions and terms related to: Inclusion, Diversity, Stereotype, Bias, Silent Collusion, and Ally; the final 4 questions were scenarios used in the *Ouch!* program (e.g., "*A friend says: Those people don't even try to speak English. You respond: You sound frustrated. What happened? Was there someone who couldn't understand?" This was an example of…*); students were asked to answer with one of the following: Ask a question; make it individual; interrupt and redirect; Say Ouch!; Assume good intent and explain the impact. Scores were tallied by the survey (in Week 5) and by the *Ouch!* program in Week 6, giving students immediate access to their quiz results; a 70% score or above was required to finish the *Ouch!* program. Finally, an open-ended follow-up question about students' comfort level was added for the study to assess pre- and post-comfort levels: *How comfortable are you in speaking up when someone says something that is offensive to you, or about other people (i.e., stereotypes, biases, racist comments, etc.)?* The research team coded the open-ended responses to indicate comfort level (0 = not at all comfortable, 1 = comfortable).

Results

Pre-assessment knowledge scores ranged from 60 to 100% and post- assessment knowledge ranged from 70 to 100%. The students' average comfort level was 44% at Week 5 and 93% at Week 6. We used a paired samples *t*-test to reflect changes in scores of the pre- to post-assessments in both knowledge and comfort level. Students' knowledge actually *decreased* (89.34% to 85.56%, $t = 2.48$, $p = .015$), while students' comfort level significantly *increased* from 44% (Week 5) to 93% at post-comfort level (Week 6), $t = -7.71$, $p < .001$.

One example of a student's Week 5 response indicated anxiety and uncertainty about speaking up: "*I would like to say I would defend myself or others in situations that I see as unfair, but I usually do not speak up. I am not confident in myself, my information, or my arguments, and I constantly over think the response to the point that I just do not do anything."* After completing the program, common student responses included: "*After the training, I feel more comfortable speaking up in various situations because I have had the proper training of how to say something in an uncomfortable situation without being rude or blaming others. It gave me many options to choose from depending on the setting and person. I am most likely to use the "assume good intent" method because I feel it is an appropriate and nice way to redirect someone and allows them to realize the impact that their words make on others";* and *"Now that I've completed the training I feel like I actually learned practical ways to respond in situations where I feel like comments are racist, bias, etc. I've never really known the correct way to go about responding in those type of situations which is where the discomfort was coming from. Now, however, I learned 6 different ways that I can act as an ally and speak up for others. I would feel more comfortable now that I'm more educated."*

Discussion

This study investigated the impact of the *Ouch! That Stereotype Hurts* program with undergraduate students. It was surprising that students' knowledge actually decreased over one week after participating in the *Ouch!* program; however, it should be noted that it was only a slight difference from 89% to 86%. Perhaps students felt less pressure in Week 5 since it was noted that their quiz was not being graded, whereas the *Ouch!* training program stated that a score of 70% was required to complete the training. Also, students participated in the pre-assessment at Week 5, likely already establishing several weeks of curriculum education on topics, such as diversity, equity, and cultural competence, which could have accounted for their initial correct responses.

The most promising finding from the training was that students' comfort level about speaking up in response to hearing a microaggression significantly increased, and substantially from 44% of students at Week 5 to 93% of students at Week 6 after participating in the training. Thus, in one week, after viewing a 30-minute training, students reported a huge shift in their comfort level to speak up in situations with aggressors. The *Ouch!* program has the potential to help both targets and bystanders become more comfortable and less uncertain on how to respond to a microaggression (Ashburn-Nardo et al., 2008).

The online platform of *Ouch!* is very versatile, allowing students to participate in online training videos and a final quiz on their own time. The program was placed on the university's learning management system which students are already familiar with. Although this study used an online training with two online diversity courses at one institution, the findings can be replicated with other delivery modes, such as in-person courses, virtual, remote, online or hybrid. This program could be applied to various educational settings, including but not limited to: high school education, student-life organizations, religious groups, study abroad or international internship experiences.

The present study's participants were drawn from a small sample of primarily white undergraduate women attending college in a Predominantly White Institution (PWI) in a mid-sized community in the mid-south in the U.S. However, some research (Hu & Kuh, 2003; Loes, Pascarella, & Umbach, 2012; Wiersma-Mosley, 2019; 2020) indicates that white students benefit in critical thinking development when they are exposed to diversity trainings and assessments. In addition, data were based on self-report pre- and post-assessments, thus there may be testing effects and other potential biases in this sample.

Future research should seek to measure the effects of the *Ouch!* program longitudinally with larger and more diverse sample sizes, rather than over one semester; as with any development, this skill may take additional effort and time to fully form. This study was conducted at a PWI that assessed a homogenous group of white students, thus future studies must also capture how students of color view and respond to

the *Ouch!* program as they are likely the targets experiencing racial microaggressions (Byrd, 2018). Additional qualitative data using reflections and interviews would help capture the full extent of all students' learning and comfort level. Finally, assessing how the *Ouch!* program impacts faculty and staff on a college campus is highly warranted. Without proper faculty and staff support in the process of unlearning biases, there remains a continued tolerance of white-dominant education and educators at PWIs, which can be detrimental to the path towards equity. It is also important to understand that microaggressions are not a single-issue problem, instead they are multifaceted and impact all levels of academia. For example, one study found that graduate students benefitted most from educators who supported and accepted them with authenticity and validation (Linder et al., 2015).

Conclusion

This study indicates that college students, especially those who identify as white, may benefit in their comfort level in speaking up against microaggressions when exposed to diversity educational training (i.e., *Ouch!*) on campuses. This study used an assessment that could be implemented online across all types of college campuses with large student enrollment to increase comfort in speaking up when addressing microaggressions. It is a valuable and innovative assessment because it is online, can be measured with multiple attempts and post-assessments, and students have immediate access to their assessment scores.

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Physical Characteristics and Classification of the Large Amplitude Variable Star V1719 Cygni

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Abstract

Pulsating stars are used as standard candles which are helpful in determining distances to stellar objects along with the relationship between their period and apparent luminosity. The focus of this study was the variable star, V1719 Cygni, which is often classified as a Delta (δ) Scuti star, but there exists debate that it should be classified as a RR Lyrae star due to its abnormal light curve and similar characteristics between the two variable star categories. Observational data was taken in 2019 using the Las Cumbres Observatory international telescope network. The resulting data were calibrated using comparison stars in the field of known magnitude. We performed aperture photometry in the V-, B-, i- and z- photometric bands. The period was then found using the string method which determines the most probable period. The average period was found to be 0.269 days with an error of 0.0005. The distance was calculated using the previously established period-luminosity relation for both δ Scuti and RR Lyrae stars to determine which classification fits our data best. The distance calculation was more closely aligned with previous results when using the δ Scuti relationship as compared to the RR Lyrae relationship. Based on these results, we conclude that V1719 Cygni should be classified as a high-amplitude δ Scuti variable star. It is important to note that period-luminosity relationships have not been established in all photometric bands, but the period measurements obtained in the B-, i-, and z- bands will help to establish that relationship.

Keywords: Pulsating star, δ Scuti, RR Lyrae, light curve, period-luminosity relationships

Profiles of the Authors

Ashley Lieber is a senior at the University of Arkansas. She will be graduating in May 2021 with a BS in physics with a concentration in astronomy. Additionally, she will earn minors in mathematics and STEM education. In the immediate future, she is planning to pursue a Ph.D. in Astrophysics to continue her work in astronomy research. She hopes one day to work in astronomy education outreach as part of an observatory or museum to share the great advancements and discoveries of space science with the general public. She has also conducted computational research in solar physics and will soon defend her honors thesis on the flaring activities of M dwarf host stars of Earth-like exoplanets. When she is not doing research, she enjoys immersing herself in the Fayetteville community by taking part in community attractions like the farmers' market, Crystal Bridges art museum, and the vast array of hiking trails and restaurants.

Logan Siems is a student at the University of Arkansas in the Master of Arts in Teaching program. She graduated from the University of Arkansas in the spring of 2021 with degrees in physics and mathematics. Now that she is a Noyce fellow, she is working and learning to incorporate aspects of authentic research experiences such as her own experiences in astronomy into secondary science and mathematics education. She also enjoys roller skating and buying plants that she will forget to water.

Introduction

Pulsating stars have come to be critical objects for measuring stellar distances due to their regular, periodic changes in luminosity. The light curves that result from these stars and their accompanying period-luminosity relationships can be used to determine distances beyond the limits of parallax.

These period-luminosity relationships have been established for the multiple types of pulsating stars in many photometric bands. RR Lyrae and Delta (δ) Scuti stars are two types of pulsating stars with distinct period-luminosity relations. However, stars of these types can occasionally be hard to differentiate from each other since characteristics such as period of pulsation, temperature, and luminosity occasionally overlap. Most stars in either of these categories have distinct periods or locations on the H-R diagram that clearly establish their classifications as either a Delta Scuti or RR Lyrae star, but sometimes stars have temperatures, luminosities, and periods that do not make the categorization clear (Catelan and Smith, 2015).

One such case is the star V1719 Cygni. This star's period and temperature do not clearly fall into either classification category thus leading to the discrepancies that are present in the existing literature. V1719 Cygni was originally categorized as a RR Lyrae star by Poretti (1984), however they found the light curve to be "unstable" on longer timescales. Poretti and Antonello (1988) studied the light curve in further detail using Fourier analysis. To account for abnormalities in the star, such as its asymmetrical light curve, they proposed various physical characteristics of the star, such as microturbulence, high metallicity, and helium settling. In the 1990s, Fernley & Barnes (1997) used the data gathered by the *HIPPARCOS* satellite (Perryman, 2011) to classify the star as an RRc Lyrae due to the observed sinusoidal light curve, corresponding period of ≈ 0.25 days and low metallicity.

Other studies of V1719 Cyg were compiled and compared by Pena et. al (2001) along with their own observations. Based on this data, especially the high metallicity and larger mass, Pena et al. concluded that V1719 Cyg is a high amplitude, Delta Scuti. However, the [Fe/H] value that they used in this study was 1.020, which is a very unlikely value according to Catelan and Smith (2015). This classification as a Delta Scuti star is significant because it determines which period-luminosity relation can be used to find an accurate distance to V1719.

A period-luminosity relationship has been established in the V-band for Delta Scuti stars (Ziaali et al., 2019) and in the V, i, and z bands for RR Lyrae type stars (Catelan et al., 2004; Cáceres and Catelan 2008). In this paper, the period of V1719 Cyg was studied in the V, i, B, and z bands which was then averaged to be used in the determination of distance. The stellar distance was determined using the previously established period-luminosity relationships for both RR Lyrae and Delta Scuti for comparison purposes. Comparing these distances provides more evidence to confirm the classification of V1719 Cyg as a high-amplitude Delta Scuti star and provides more data that can be used to solidify and establish period-luminosity relations for Delta Scuti star in the V, B, i, and z bands. These period-luminosity relations are a very active field of current research which will help to more accurately establish distances to distant objects.

Methods

I. Observations

In order to investigate the behavior of the variable star V1719 Cyg, we remotely requested photometric data of the star which was carried out by the 0.4-meter SBIG (Santa Barbara Instrument Group) telescope at the Haleakalā Observatory in Hawai'i. The summit where the telescope is located operates under conditions that are optimal for making ground-based observations of the night sky such as its altitude, limited light pollution, dryness, and stillness of air. Observations were conducted through the Las Cumbres Observatory Telescope Network which consists of 23 international telescopes that work in conjunction with the Our Solar Siblings project. The coordinates at the time of this investigation were Right Ascension of

21h 04m 34.40s and Declination of +50d 47m 07.50s. Data was recorded over a time span of thirty-three days starting in November 2019 yielding a total of thirty-eight observations. The data was collected in four photometric bands: i, z, B, and V. These bands cover a broad range of the electromagnetic spectrum from infrared to visible light which were highly useful in our aperture photometry conducted later on.

II. Apparent Stellar Magnitude

The data from the observatory was preprocessed through the Our Solar Siblings (OSS) data pipeline as described in Fitzgerald (2018). Images were processed using the OSS pipeline including techniques such as image cleaning, calibration, and various aperture photometry and point-spread function photometry (PSF) algorithms. Aperture photometry methods given by the apt, sek, and apt files measure the flux inside of some circle for each object in the field and they tend to work better for more isolated stars such as V1719 Cyg. Because of this, we expected to have more success analyzing data from these files. Alternatively, point spread function (PSF) photometry methods given by the dop, dao, and psx files fits a function to each object and so it manages close objects and crowded fields better than the aperture methods (Fitzgerald 2018). Interestingly, for the i and z band we utilized the apt files, but for the B-band, we used dao and for the V-band we used sek. This was because these files proved to be more compatible with the Python script used for analysis later on.

With the optimal photometry tool determined for each band, the light curves for each observed band of data could be constructed. This was done by employing an established nine-stage pipeline of Python code. This code systematically removes any damaged or useless data that are outside a certain threshold using Astrosource. For example, if a certain image does not have clear images of the surrounding star field in order to make comparisons in relative magnitude, the image will be discarded. The code identifies stars near our target star, V1719 Cyg, to use for comparisons. These stars met the criteria of being present in every image over the data collection period while also remaining relatively constant in apparent magnitude over that same period. Then the apparent magnitude of V1719 Cyg could be compared to these stars to determine how it varied over time relative to these stars with relatively constant apparent magnitude as described in Fitzgerald (2018). These comparison stars create a baseline in magnitude to which the variations in the target star can be more accurately calibrated.

III. Light Curve and Period Analysis

The period of pulsation was then determined using the phase dispersion method (PDM) and distance method (also known as the string-length method) (Stellingwerf, 1978; Dworetsky, 1983). The PDM method tests various period candidates by using the period to compare variance of the amplitude in bins along the phase and finding the period for which the variance is minimized (Stellingwerf, 1978). The distance method also uses candidate periods and plots amplitude vs phase then finds the period with the minimum distance between consecutive points (Dworetsky, 1983). After the period was determined in each band, the variation of the target star over its phase was graphed which is known as its light curve.

The variation in V1719 Cygni's magnitude throughout its period was then graphed and is known as the star's light curve. In this study, two complete cycles were graphed in the light curve to demonstrate the repetitive nature of the star's variations in magnitude.

Results

I. Apparent Magnitude Results

The apparent magnitude of the star in each band studied is reported in Table 1 along with the uncertainty in measurements and amplitude. The value reported as the apparent magnitude is the middle

magnitude which is the midpoint within the magnitude variation as seen in the light curves of Figures 1, 2, 3 and 4. It is interesting to note that the values for amplitude are considered high for a Delta Scuti type variable star (Catelan and Smith, 2015), which may be a contributing factor to its misclassification.

Table 1:
Stellar Magnitude and Amplitude in Each Photometric Band Studied

	z- Band	i- Band	B- Band	V- Band
Magnitude (mags)	7.67	7.67	8.093	7.849
Amplitude (mags)	0.256	0.256	0.547	0.765
Uncertainty[1]	0.02768	0.0207	0.0109	0.0207

[1]Value of uncertainty relates to the measurements themselves

Table 1: Table details the apparent magnitude, amplitude, and uncertainty of measurements resulting from this study of V1719 Cyg. Values in each band are reported. The apparent magnitude refers to the middle or mid-point magnitude across all measurements within a certain band.

II. Period and Light Curve Results

The period of V1719 Cyg was determined in each photometric band studied. Both the PDM and distance (string) methods were used to calculate these values which are reported in Table 2. In order to evaluate this calculated period in relation to previous studies, Table 3 provides a comparison of previously determined periods of V1719 Cyg to the period reported in this paper. This direct comparison shows that the period reported in this study is comparable to the previous determinations of period thus providing more evidence towards the validity of our methods and the findings. It is important to note that of the two periods obtained in each band using the two methods described, the period used for calculation purposes was chosen on the basis that it agreed with the period in the remaining bands and had a considerably low error.

These calculated periods were then used to graph the light curve of the star in each photometric band as seen in Figure 1, 2, 4, and 4. The graphs show two complete periods to show the periodic variability of this star. It should be noted that the error in the periods displayed in Table 2 are underestimated as a consequence of the instruments and code that was used (Fitzgerald, 2018).

Table 2:
Period Determinations in Each Photometric Bands

	z- Band	z- Band Error	i- Band	i- Band error	B- Band	B- Band Error	V- Band	V- Band Error
Period[1] (days)	0.21416	0.00055	0.3152	0.0015	0.2671	0.0014	0.26704	0.00084
Period[2] (days)	0.37536	0.00016	0.20344	0.0001	0.277	0.0005	0.26656	0.0008

[1] Determined using the Distance (String) Method
[2] Determined using the PDM Method

Table 2: Table details the period and period errors of V1719 Cyg in each photometric band used in this study.

Table 3: Comparison of Previous Findings of Period to this Study	
Reference	Period (days)
Padalia & Gupta 1982	0.267394
Poretti 1984	0.267298
Poretti & Antonello 1988	0.267295
Present Paper	0.27323

Table 3: Table compares the period used in calculations for this study with the period findings of previous studies.

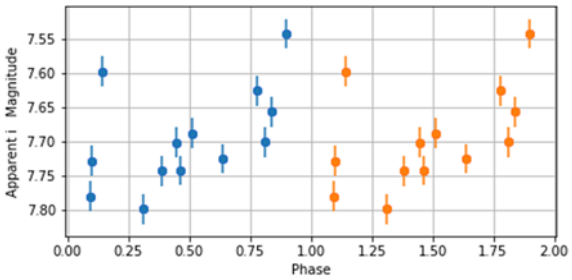

Figure 1: Light curve spanning two complete phases for V1719 Cyg in the i-band using the PDM period.

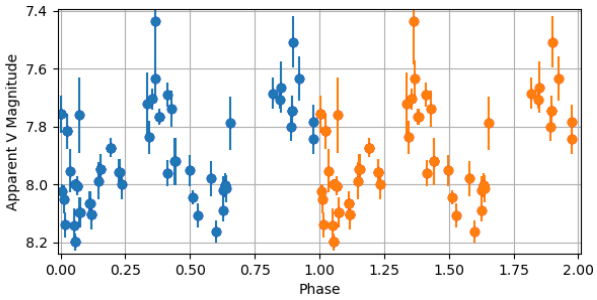

Figure 2: Light curve spanning two complete phases for V1719 Cyg in the V band using the PDM period.

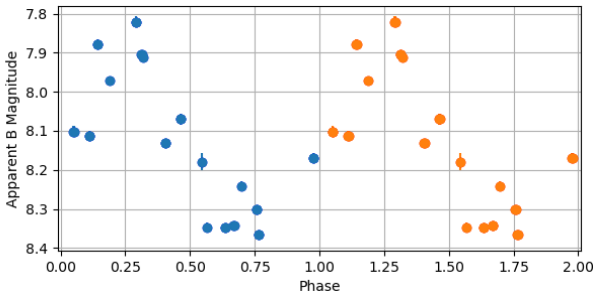

Figure 3: Light curve spanning two complete phases for V1719 Cyg in the B band using the PDM period.

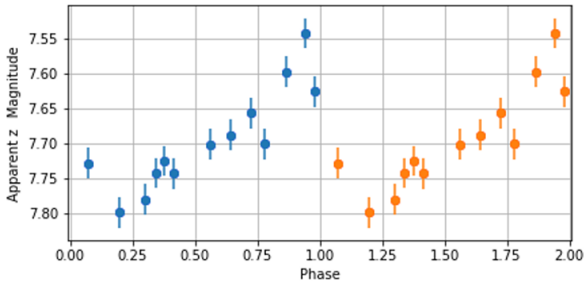

Figure 4: Light curve spanning two complete phases for V1719 Cyg in the z band using the PDM period.

III. *Absolute Magnitude and Distance Results*

Finally, the distance to V1719 was calculated using the values we established for period and apparent magnitude, in the V, I, and z bands along with the established measurement of metallicity for V1719 Cyg from Kim and Yushchenko (2011). This metallicity value [Fe/H] of 0.300 accounts for the chemical composition of the star and was converted to the logarithm of the of the metal mass fraction, log Z using the following relations from Cáceres and Catelan (2008) and an [α/Fe] value of 0.3 as suggested in Catelan et al. (2004).

$$\log Z = [\mathrm{M/H}] - 1.756$$

$$[\mathrm{M/H}] = [\mathrm{Fe/H}] + \log(0.638f + 0.362)$$

where $f = 10^{[\alpha/Fe]} = 10^{0.3}$

Then, absolute magnitude, M, could be found using period-luminosity relations for RR Lyrae stars in those bands, which are shown in the equations below. The V-band relation comes from Catelan et al. (2004). The i and z band relations come from Cáceres and Catelan (2008).

$$M_v = 2.288 + 0.882 \log Z + 0.108(\log Z)^2$$

$$M_i = 0.908 - 1.035 \log P + 0.220 \log Z$$

$$M_z = 0.839 - 1.295 \log P + 0.211 \log Z$$

Then, the calculation was repeated using the relation established in 2019 for Delta-Scuti type stars in the V-band, shown in the equation below (Ziaali et al., 2019).

$$M_V = (-2.94 \pm 0.06) \log(P) - (1.34 \pm 0.06)$$

Once the absolute magnitude was found, the distance could then be calculated using the following equation

$$d = 10^{(m-M-A+5)/5}$$

where d is the distance, m is the apparent magnitude, M is the absolute magnitude, and A is the extinction factor that accounts for interstellar reddening which results from the scattering of starlight in the interstellar medium (Fitzgerald, 2018). The results of these calculations are shown in Table 4 alongside a comparison to previously published results.

Table 4:

Distance to V1719 Cyg: Comparison of Previous Findings to this Paper

Reference	Distance (pc)	Error
Gaia (2016)	392.512	±5
Joner & Johnson (1985)	158	N/A*
Johnson & Joner (1986)	325	N/A*
Alania (1987)	223	N/A*
Claret & Rodriguez (2000)	283	N/A*
Pena et al. (2001)	324	±53
Present Paper: Delta Scuti V-Band[1]	316.68	±5.6
Present Paper: RR Lyrae V-Band[2]	228.03	±14.4
Present Paper: RR Lyrae z-Band[2]	141.17	±5.7
Present Paper: RR Lyrae i-Band[2]	149.69	±6.1

[1]Using period-luminosity relation outlined in Ziaali et al (2019)

[2]Using period-luminosity relation outlined in Catelan et al. (2004) and Cáceres and Catelan (2008).

*Errors in these cases could not be found

Table 4: This table displays the results of the distance to V1719 Cyg determined in this study alongside previously published findings of distance. The corresponding errors are also reported except for the cases where errors could not be found or substantiated (these are indicated by *)

If V1719 Cyg was an RR Lyrae type star, we would expect the estimations of distance in each band using the RR Lyrae relations to agree rather closely with one another. However, as seen in RR Lyrae distance determinations in Table 4, the values vary by nearly 100 parsecs from the V-band to the z-band. This provides evidence in support of the conclusion that V1719 Cyg is not an RR Lyrae star. On the contrary, the distance determined by using the Delta Scuti relation is 316.68 $\pm$ 5.6 pc which is closer to agreeing with the distance found by *Gaia* (2016) – 392.51 $\pm$5 pc – by the parallax method, though they do not align perfectly showing a difference of 76 parsecs.

It should be noted again that the errors in the calculations of distance are yet again underestimated. One of the contributing factors for the underestimation of the errors is due to the algorithm used to analyze the photometry files itself. It is noted that the code consistently underestimates the error as it aims to calibrate the photometric images of the star that are inputted (Fitzgerald, 2018). This underestimation of the error at the period determination stage would have been propagated into the errors in the distance calculations. While refining the code is outside the scope of this project, it is always a goal to strive towards.

The differences seen in these distance calculations showcase the fact that the star V1719 Cyg is a special case to study. It's abnormal properties – temperature, metallicity, luminosity, and high amplitude – contribute to its misclassification (Peña et al., 2001). There is still much work to be done to further confirm the classification of this star and the validity of the Delta Scuti period-luminosity relation (Ziaali et al., 2019). Since a period-luminosity relation for Delta Scuti stars has not been established for bandpasses other than V, the measurements of period in the B, i, and z bands and the distance estimation using the relatively new relation in the V-band can provide useful insight on how these relations behave as future studies seek to establish them.

Conclusions

This research has determined the magnitude of the variable star V1719 Cyg in different photometric bands to be as follows, V: 7.849, B: 8.093, i: 7.67, z: 7.67. The period was also determined using the Distance Method and Phase Dispersion Method. From the values of period in these bands, an average period of 0.27323 days was found which supports the previous findings of the period for this star.

The distance calculations using the RR Lyrae period-luminosity relation are, V: 228.03 $\pm$ 14.4 pc, i: 149.69 $\pm$ 6.1 pc, z: 141.17 $\pm$ 5.7 pc. When the calculations were done using the Delta Scuti period-luminosity relationship, the V band yielded a distance of 316.68 $\pm$ 5.6 pc. These distances can be compared to the distance provided by *Gaia* which is 392.51 $\pm$5 pc (*Gaia* Collaboration, 2016). The data clearly supports the statement that the star V1719 Cyg is more accurately classified as a large amplitude Delta Scuti star rather than an RR Lyrae type star.

Throughout the course of this study, it became apparent that physical characteristics of V1719 Cyg such as its period, light curve, and calculated distances, and the methods used to study such variable stars may be the root cause for the misclassification of the star as a RR Lyrae variable star. A more detailed study into the surface gravity and metallicity of this star should be conducted to better differentiate between RR Lyrae and Delta Scuti stars. However, based on the findings in this study, we concur with recent results that V1719 Cyg should be classified as a large amplitude, Delta Scuti variable star though we recognize the need for the development of more period-luminosity relations in more bandpasses for Delta Scuti type stars.

Acknowledgments

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The Effects on Employees from the Switch to Mandatory Contributions in the University of Arkansas Retirement Plan

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Abstract

After the 2016 fiscal year, the University of Arkansas Retirement Plan instituted mandatory contributions for full-time employees, presumably to boost retirement savings among those least prepared for retirement. Mandatory contributions began at 1% in fiscal-year 2017 and increased annually to 5% in fiscal-year 2022. This change may have harmed employees with tight budget constraints who wish to contribute less than the minimum contribution rate. At the same time, it may have helped those who were saving less than their optimal amount due to behavioral biases. We surveyed employees at the University of Arkansas campus to assess the effects from the change to mandatory contributions and received 171 responses. Our main findings are that most respondents are unaffected by the change to mandatory contributions; a small minority are unsatisfied with the change; average contribution rates increased for all full-time employees, especially staff; a small percentage of staff, but no faculty, may have been harmed by the change; and a larger percentage of staff and faculty may have been helped. These results, however, must be interpreted with caution because they are limited by a relatively small sample size that is not representative of the employee composition at the University of Arkansas. For more robust results, a much larger survey is needed that reaches across all campuses of the University of Arkansas System to accurately assess the effects on employees from mandatory contributions.

Keywords: retirement savings, mandatory contributions, behavioral biases, inertia, loss aversion, present bias, budget constraints

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Introduction

Many Americans either contribute too little or wait too long to save for retirement, which forces them to live on a fraction of their income earned before retiring. A 2019 survey from the National Institute on Retirement Security (Oakley & Kenneally, 2019) shows that 75% of Americans believe there is a retirement crisis, and millennials are the most concerned about their financial security in retirement. Another report from the National Institute on Retirement Security (Rhee, 2013) estimates that 45% of working-age households have no retirement account assets, 92% do not meet conservative savings targets for their age and income, and only 52% of working-age households participate in a workplace retirement plans. In addition, the National Retirement Risk Index published by the Center for Retirement Research at Boston College shows that 49% of households in 2019 were at risk of not being able to maintain their pre-retirement standard of living in retirement. (Munnell, Chen, & Siliciano, 2021)

Saving too little for retirement can either be a rational (optimal) or irrational (suboptimal) decision. All households are budget constrained to some extent, meaning they must choose a savings rate that balances current consumption versus future consumption in retirement. Those who are severely budget constrained may not have the ability to contribute to retirement at all beyond Social Security taxes because they need all their disposable income for present day consumption. Others may choose to divert some of their income for retirement even though they know the amount is insufficient to fund the retirement lifestyle they would prefer. Others have the income that allows them to save enough to live comfortably in retirement. If these decisions are made with careful thought and with the best information available, then such savers are acting rationally. They are optimizing their retirement savings, even if it means not saving at all or saving too little to be prepared for retirement.

In contrast, an individual or household can irrationally choose to save too little for retirement, which leads to a suboptimal outcome. A behavioral bias exists when an individual makes a less-than-optimal decision given the available information because of a bias in the decision making. Three behavioral biases can lead people to voluntarily save too little even though they would prefer to save more. The first bias is *inertia*. Many people realize they need to increase saving for retirement, but they procrastinate until nudged or forced to do so. Second is *loss aversion* where the perception of a loss of a certain amount hurts more than the pleasure derived from an equal gain. This bias prevents some people from increasing their retirement saving because the intense pain of seeing their paycheck go down outweighs the pleasure of equal financial returns in the future. A purely rational decision would lead these people to save more. The third bias is *present bias*. People acknowledge a need to save more and may even make a non-binding pledge to doing so in the future, but as the future draws nearer, their preference for consumption in the present becomes increasingly stronger, which ultimately overcomes their desire to save. People with strong present bias have low self-discipline in the present moment.

After the 2016 fiscal year (FY), which ended June 30, 2016, the University of Arkansas enacted changes to the retirement plan, presumably to address low savings rates among some employees.[1] Beginning in 2017, the University of Arkansas Retirement Plan required all full-time employees to make a mandatory retirement contribution of 1% of salary. This contribution rate increased by one percentage point every fiscal year to 4% in 2020. The final increase to 5% was originally planned for 2021, but the university delayed that increase one additional year with the onset of COVID-19. As of July 1, 2021 (FY 2022), employees must contribute the minimum rate of 5%. The university matches employee contribution rates up to a maximum of 10%, so full-time employees that contribute the minimum rate in 2022 have a combined saving rate of 10% of their income, a large increase relative to those that chose not to participate in the program prior to 2017.

The change to mandatory contributions may have harmed some employees while making others better off. The main concern with mandatory contributions is that they harm individuals with tight budget constraints who wish to contribute less than the minimum contribution rate. Mandatory contributions are harmful to such employees because the reduction in utility from the decline in current consumption outweighs the increased utility from the additional retirement savings. These employees would view the minimum rate as too high, leading to suboptimal savings because they are unable to reduce the contribution rate to the rational rate they would choose without the mandate.

On the other hand, mandatory contributions may have benefitted some employees because behavioral biases prior to the change in the retirement plan caused them to have suboptimal savings rates that were too low.[2] For those with inertia, the rollout of the new plan may have raised awareness among the procrastinators to actively choose a more optimal contribution rate. Even if they did not take explicit action, the increase in the savings rate from mandatory contributions may have brought them closer to their optimal contribution rate. For employees with intense loss aversion, an increase in mandatory contributions would force them to save more optimally. With employer matching and tax benefits, a 1% increase in the contribution rate leads to an increase in savings of more than 2%. Finally, mandatory contributions would force those with present bias to make a more optimal trade-off between current consumption and future consumption by overcoming their inability to make a rational decision in the present moment. In sum,

[1] The University of Arkansas fiscal year begins July 1 of the preceding calendar year and ends June 30 of the current calendar year. For example, FY2020 began July 1, 2019 and ended June 30, 2020. Reference to a year in this report is to the fiscal year.

[2] Apart from behavioral biases, some employees wishing to maximize their retirement savings may have benefited from mandatory contributions due to an easing of regulatory constraints. Employees who were previously unable to save at their optimal rates due to Internal Revenue Code 402(g), which limits the amount of elective deferrals a participant may exclude from taxable income, would have benefitted because required contributions are exempt from 402(g), which effectively raises the contribution limit. Analysis of this effect, however, is beyond the scope of our paper.

mandatory retirement savings can increase saving rates to more optimal levels for many employees because it nudges or forces them to overcome at least partially each of these three biases.[3]

We document the effects on full-time employees from the changes to the University of Arkansas Retirement Plan. We designed and conducted a survey (see Appendix A) of full-time employees at the University of Arkansas.[4] The survey tracks annual contribution rates between 2016 and 2020 and identifies those that do not believe their retirement savings are optimal either because their contribution rates are too low or too high. Our objectives are to describe the impact of mandatory contributions on employee retirement savings, and to assess the degree to which employees have been helped or harmed. Those that have been harmed are relatively easy to identify because they would be contributing at the minimum rate (4% in 2020) and view their contribution rate in 2020 as 'too high.' Tight budget constraints rather than behavioral biases should account for the belief that their contribution rate is too high. Alternatively, those that have been helped would have increased their retirement contributions between 2016 and 2020, whether voluntarily or by force, because mandatory contributions helped them overcome behavioral biases. These employees would view their contribution rate in 2020 as 'just right,' and they should exhibit strong behavioral biases. Our main findings are the following:

1. Most survey respondents are unaffected by the switch to mandatory contributions. Of the 102 respondents that were employed prior to the change and reported all five years of contribution rates, 72% (92% of faculty and 59% of staff) contributed 10% or more to their retirement account in Fiscal Year 2020.
2. A large majority of respondents (89%) are either satisfied or indifferent to the change to mandatory contributions. Just 7% of faculty, and 15% of staff are not satisfied with the changes. In addition, 75% of faculty, and 64% of staff agree they are adequately prepared for retirement given their current contribution rates. However, a sizable minority of staff (28%) disagree with this viewpoint.
3. Average contribution rates increased for all full-time employees, especially staff, after the switch to mandatory contributions. The average contribution rate for staff increased by 100 basis points to 8.2% between 2016 and 2020. We estimate that the average staff member at the University of Arkansas in 2020 increased annual retirement contributions by $1,266 including the employer match relative to the contributions they would have made without the switch to mandatory contributions. The average contribution rate for faculty increased by 30 basis points to 10.1%.

[3] These same behavioral biases could also lead to contribution rates that are too high. An employee may set a contribution rate of 10%, for example, but then a spouse is laid off, and inertia prevents the employee from reducing the contribution rate. However, if the optimal contribution rate is equal to or greater than the minimum required rate, the change to mandatory contributions has no effect. If the minimum required rate is binding, the harm to the employee results from budget constraints rather than behavioral biases.

[4] The survey received University of Arkansas IRB approval June 4, 2020 with Protocol # 2002247755.

4. A small percentage (3.5%) of staff, but no faculty, may have been harmed by the switch to mandatory contributions. These staff respondents perceive their 2020 contribution rate of 4% (the minimum) as 'too high.' They exhibit tight budget constraints and present bias. The power of statistical testing, however, is too weak to confirm these results.
5. A much larger percentage of staff (16%) and faculty (11%) may have been helped by the switch to mandatory contributions. These respondents increased their contribution rates at some point between 2016 and 2020 either voluntarily or by force, and they view their contribution rates in 2020 as 'just right.' These employees exhibit signs of inertia and present bias, and the staff also exhibit signs of loss aversion. Again, the power of statistical testing is too weak to confirm these results.

The results of this study must be interpreted with caution because they are limited by a small sample size. The 172 total responses may be insufficient to draw statistically significant inferences from a population of 4,593 full-time employees.[5] This problem is exacerbated even further by the few respondents that were harmed by the change to mandatory contributions. Just three respondents reported that their contributions rates were too high. A statistically reliable sample would require at least a ten-fold increase in the number of staff surveyed.

A second concern is that the survey respondents are not representative of the employee composition at the University of Arkansas. Roughly 10% of university employees work in the Sam M. Walton College of Business, but 62% of the respondents work there, so the results disproportionately represent Walton College employees. This disconnect results from our inability to solicit responses from all full-time employees via email. The survey was released in the summer of 2020, but we were able to email the survey only to Walton College employees. To reach employees in other colleges, the survey announcement was posted on the University's online Newswire publication, but this indirect approach sharply reduced the response rate. The primary concern from the disproportionate representation of business school respondents is that the average faculty salary in the college is higher than the average faculty salary in other colleges. The bias arising from staff responses should be much smaller because average staff salaries are more equal across the campus. A much larger survey is needed that reaches across all campuses of the University of Arkansas System to accurately assess the effects on employees from mandatory contributions.

Hypotheses

In this section, we state the hypotheses and describe the theory for why the implementation of mandatory contributions may have helped or harmed certain employees.

[5] University of Arkansas Quick Facts, accessed March 2021 at https://www.uark.edu/about/quick-facts.php.

Hypothesis 1: The switch to mandatory contributions in the University of Arkansas Retirement Plan has made some employees better off because mandatory contributions nudged or forced them to overcome behavioral biases that led to savings rates that were lower than optimal.

Three behavioral biases can lead to suboptimal contribution rates that are lower than the optimal rate (Thaler & Sunstein, 2009; Thaler, 2015).

1. *Inertia*. People with inertia know they need to save more or start saving "soon" for retirement, but they procrastinate and may not act until nudged or forced to do so. Benartzi and Thaler (2013) state that almost a quarter of employees with access to an employer-sponsored plan fail to join. Madrian and Shea (2001) find that after companies switch to automatic enrollment from affirmative enrollment, participation in the retirement program is much higher, and many participants stick with the default contribution rate chosen by the company. Consequently, University of Arkansas employees with low savings rates driven by high inertia will benefit from the increase in mandatory contributions.
2. *Loss aversion.* People hate to see their paychecks go down, which happens when the retirement saving rate increases. Loss aversion means that an individual feels the pain from the loss of $1 more than the joy from a gain of $1. Although most people experience loss aversion to some extent, the loss aversion required to forego matching contributions must be at least 2 to 1 because an additional $1 reduction in the paycheck is offset by $2 in savings. Moreover, the gain to loss ratio may be greater than two-to-one because the additional savings reduces current taxes because the savings are tax deferred. Consequently, those forced to overcome loss aversion due to mandatory contributions will benefit financially in the long run.
3. *Present bias*. Although people differ in their intertemporal consumption preferences, the preferences of those with present bias change quickly as the future draws nearer. The behavioral effect is that people have more self-control when they make binding decisions now regarding actions they will take in the future rather than making decisions about the future only in the present. Planning to save money in the future is an easy thought, but actually increasing the savings rate in the present moment is much harder. People with strong present bias have less self-control to delay consumption when forced to make the choice, so they should benefit from a mandatory contribution retirement plan that boosts savings.

Regardless of the source of the bias, the survey respondents that benefitted from the program change would have increased their retirement contributions between 2016 and 2020, and they would view their contribution rate in 2020 as just right. They should also exhibit strong behavioral biases after controlling for budget constraints.

Hypothesis 2: The switch to mandatory contributions in the University of Arkansas Retirement Plan has made employees that are severely budget constrained worse off because their contribution rates are too high and cannot be lowered to the optimal rate. The disutility of the reduction in current consumption exceeds the utility of the additional savings.

Many people use their entire paycheck to purchase necessities and they have no desire to shift disposable income into retirement savings because the reduced consumption is painful and outweighs the future monetary gains in retirement. Mandatory contributions make these people worse off. These individuals would view their required contribution rate as too high, contribute the minimum rate to the retirement plan in 2020, and exhibit tight budget constraints after controlling for behavioral biases.

One alternative to mandating participation in retirement plans is to encourage employees to join the plan or increase contribution rates through social (peer) comparisons. The evidence, however, is mixed. Raue, D'Ambrosio, and Coughlin (2020) find support for upward social comparisons (comparing the saver to peers with more/better savings). Participants in an experiment who were told that their savings decision were poor in the first round were more likely to change their savings rates, and to revise them upward more than those categorized as better performers. Gunaratne and Nov (2015) also find that social comparison can improve an individual's asset allocations, but receiving advice from an expert is a more effective approach. Finally, a field experiment of a 401(k) plan provided peer information to randomized recipients that did not participate in the plan (Beshears, Choi, Laibson, Madrian, & Milkman, 2015). The information presented either the fraction of coworkers participating in the plan or the fraction contributing at least 6% to the plan. The upward social comparisons, however, led to a decrease in retirement savings of the nonparticipants.

Summary Statistics

In this section, we present key summary statistics from the survey, first for all respondents and then separately for faculty and staff. We assess employees' perceptions of the retirement plan and examine the prevalence of behavioral biases and budget constraints.

All Respondents

The survey solicitation received 172 responses from full-time employees at the University of Arkansas where at least one question was answered. The number of responses to a particular question varies depending on how many respondents chose to answer that question. The first several questions gather demographic information shown in Figure 1. Of the respondents, 62% are female and 93% are white. By job classification, 54% are staff, 41% faculty, and 5% administrators. The most common age

concentration is 51-60 at 28% of all responses, followed by 31-40 at 24%. The least common age group is those less than 30 years of age (9%). A majority (63%) of respondents work in the Sam M. Walton College of Business, reflecting easier survey access to business school employees. Finally, most respondents (65%) began full-time employment before 2017 meaning they were employed prior to the retirement plan's change to mandatory contribution. Another 5% started in 2017, and roughly 10% started each year from 2018 to 2020.

Figure 1. Survey Demographics

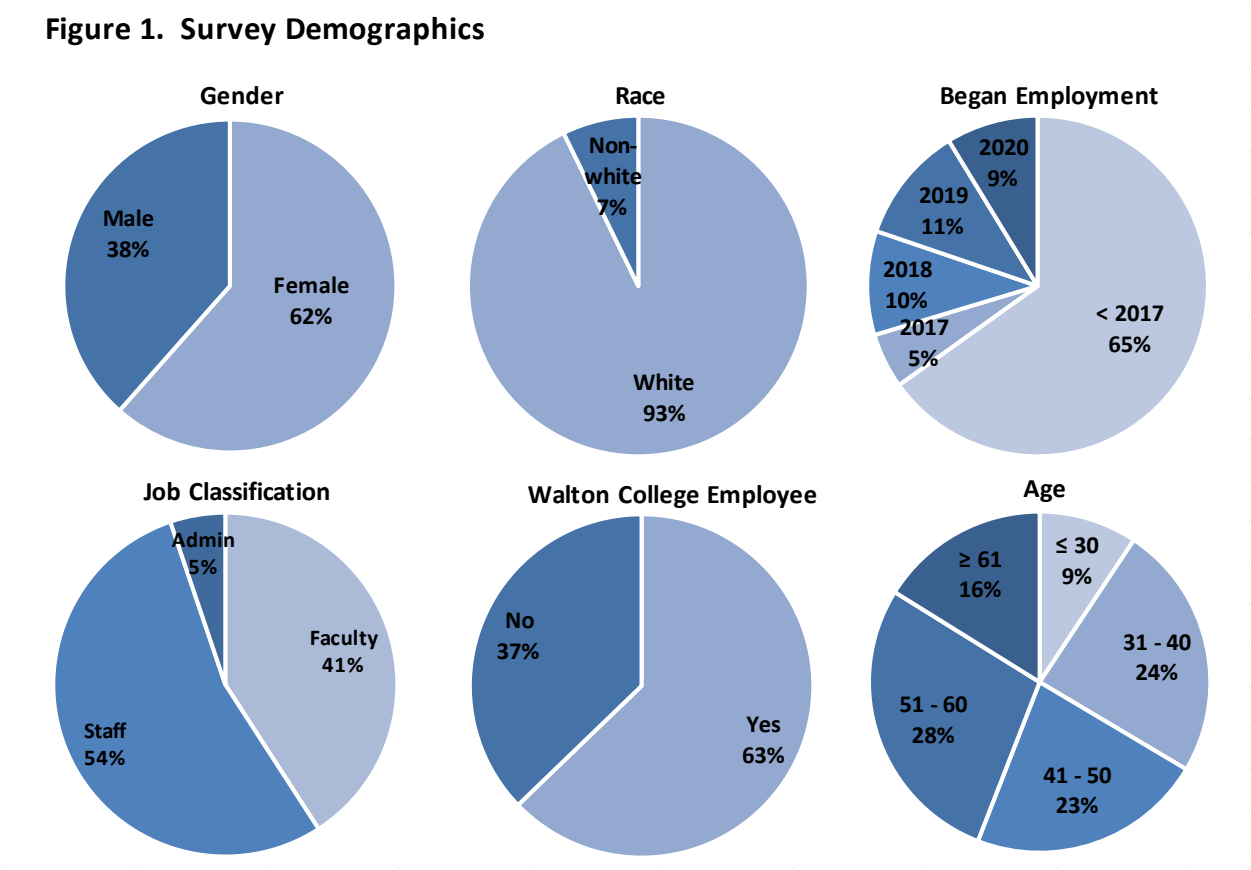


Table 1. Summary Statistics by Job Classification

Gender	N	Male	Female			
Faculty	78	56%	44%			
Staff	91	23%	77%			
Age	N	≤ 30	31 - 40	41 - 50	51 - 60	≥ 61
Faculty	72	4%	18%	25%	28%	25%
Staff	89	13%	29%	20%	28%	9%
Income	N	<$25K	$25K-50K	$50K-75K	$75K-100K	>$100K
Faculty	78	1%	6%	10%	13%	69%
Staff	91	2%	58%	21%	14%	4%
Little Disposable Income		N	Agree	Indifferent	Disagree	
Faculty		73	12%	18%	70%	
Staff		85	51%	6%	44%	

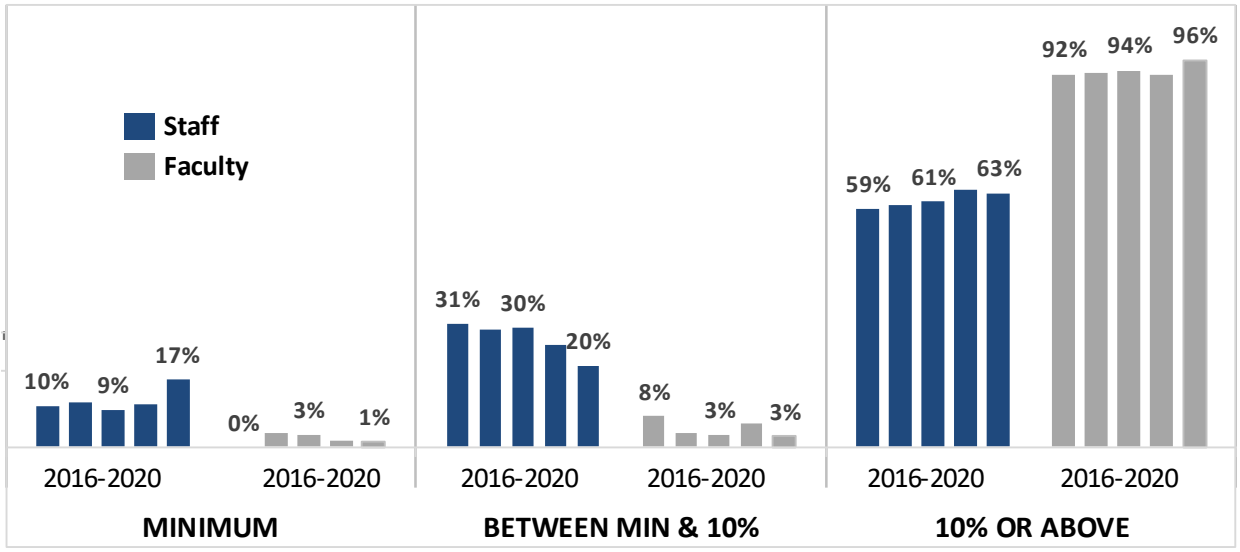
Faculty and Staff

We report several summary statistics separately for faculty and staff because gender, age, income, and education are quite different, which could affect contribution rates and budget constraints. Given the low number of responses by administrators (9) and their similarity with faculty profiles, we aggregate the two groups throughout the study and refer to them collectively as 'Faculty.'[6]

Table 1 presents select summary statistics of the survey respondents by job classification. The majority of faculty (56%) are male, but 77% of staff are female. Faculty are older than staff on average; 25% of faculty are older than 60 years of age compared with 9% of staff. In addition, 22% of faculty are less than 40 years of age relative to 42% of staff. Most staff (58%) earn between $25,000 and $50,000 in annual income while most faculty (69%) earn $100,000 or above. Given this wide pay gap, a decrease in take-home pay from mandatory contributions will harm staff more than faculty, and staff are more likely than faculty to be budget constrained. Half the staff, but just 12% of faculty agree with this statement: "After paying for necessities each month I have very little disposable income."

[6] Relative to staff, faculty profiles are more like administrator profiles on most measures. On average, faculty and administrators have similarly high contribution rates. Both groups are older than staff, more likely to be male, and have much higher incomes. Interestingly, faculty and staff are more similar to one another in their behavioral bias measures than they are to administrators. Administrators tend to procrastinate more, but they are less prone to loss aversion and present bias.

Figure 2. Percentage of Respondents by Contribution Rate, 2016-2020



Most respondents take full advantage of the employee matching benefit provided by the university retirement plan. Figure 2 displays the percentage of staff and faculty, respectively, by contribution rate buckets for the years 2016 through 2020. Nearly all faculty (96%) and a majority of staff (63%) contributed at least 10% (the maximum rate for employer matching) to their retirement accounts in 2020. A significant minority of staff, however, contribute the minimum to the retirement plan. In 2016, the year before the introduction of mandatory contributions, 10% of staff respondents did not participate in the retirement plan. A similar percentage contributed the minimum rate through 2019, but the number jumped sharply to 17% in 2020 when the minimum rate was 4%. That jump, however, is misleading because it ignores the percentage of respondents in prior years that had contribution rates less than or equal to 4%. In 2016, for example, 22% of staff respondents had contribution rates of 4% or less, five percentage points higher than the 17% of respondents in 2020.

Figure 3. Average Contribution Rates

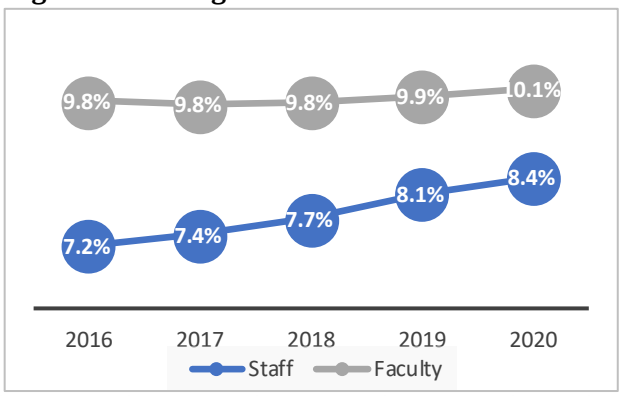
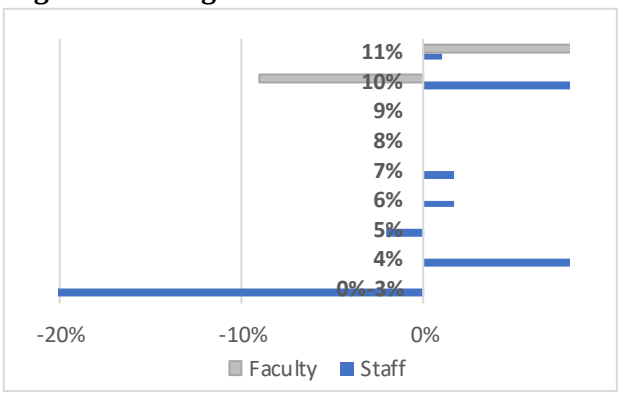


Figure 4. Change Between 2016 and 2020



Mandatory contributions have led to higher average retirement savings rates. Figure 3 plots the average contribution rates by year of faculty and staff, respectively, that were employed prior to 2016. The average contribution rate for faculty increased by 30 basis points between 2016 and 2020 to 10.1% while the average rate for staff increased by 120 basis points to 8.4%.[7] Assuming that the contribution rates and income brackets of the respondents are representative of the 3,300 full-time staff as a whole, we estimate that the average staff member at the University of Arkansas who earned a salary in 2020 of $52,709, increased retirement contributions by $633, which was matched by an additional $633 for a total increase of $1,266 relative to retirement contributions that would have occurred if the switch to mandatory contributions did not occur. (See Appendix B for the details of this computation.)

Figure 4 shows why retirement contributions increased between 2016 and 2020. The figure plots the change between those years in the percentage of respondents hired prior to 2016 that selected a particular contribution rate. The increase in the average contribution rate by faculty resulted primarily from a shift in contributions of 10% to contributions greater than 10%. The share of faculty contributing 10% declined by 4 percentage points while the share contributing more than 10% increased by 6 percentage points. The increase by staff, in contrast, resulted primarily from a shift in contribution rates of 3% or less to contribution rates of 4% and contribution rates of 10% or above. The share of staff contributing 3% or less declined between 2016 and 2020 by 20 percentage points, while the share contributing 4% increased 10 percentage points. In addition, the share contributing 10% or more increased by 8 percentage points.[8]

Figure 5. Satisfied with Retirement Plan

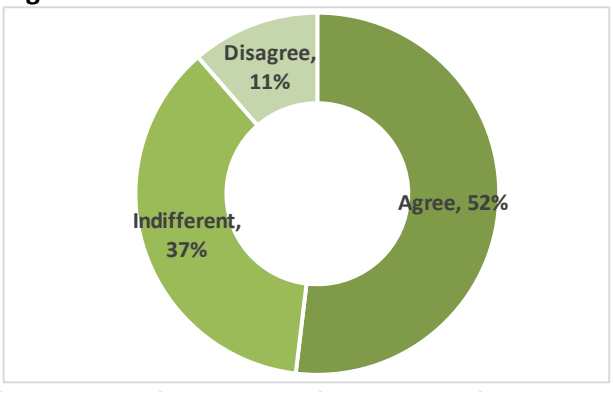
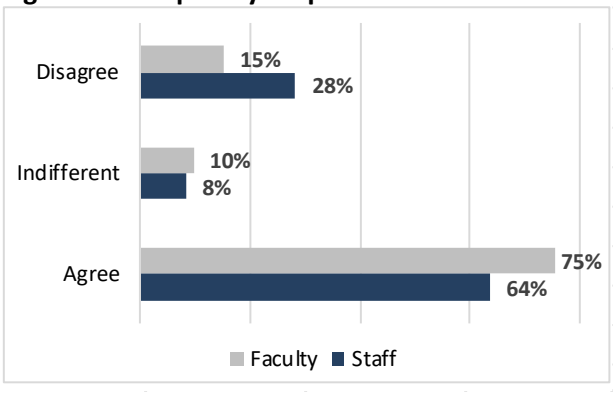


Figure 6. Adequately Prepared for Retirement



[7] When all staff respondents are included regardless of the year they began employment, the increase in the average contribution rate between 2016 and 2020 is 100 basis points to 8.2%.

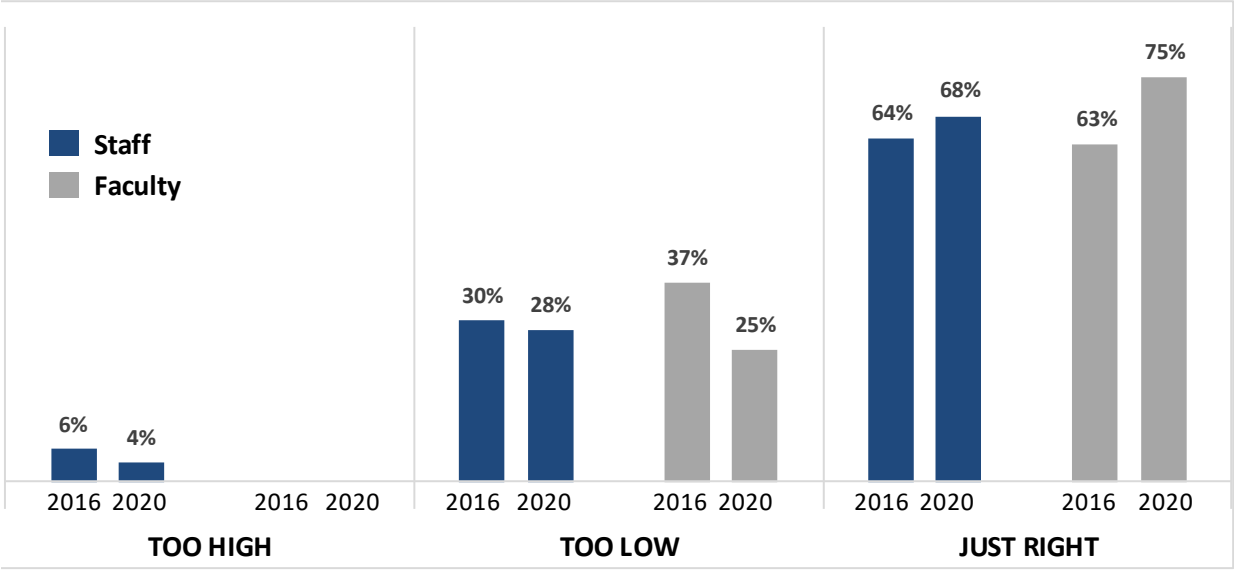
[8] The share of all staff respondents contributing 3% or less declined by 20 percentage points between 2016 and 2020, while the share contributing 4% increased by 15 percentage points, and the share contributing 11% or more increased by 4 percentage points.

Perceptions of the Retirement Plan

Several survey questions asked all respondents their perceptions of the retirement program. As Figure 5 shows, a large majority of full-time employees (89%) are either satisfied or indifferent to the change to mandatory contributions. Just 7% of faculty, and 15% of staff are not satisfied with the changes. In addition, Figure 6 shows that 76% of faculty, and 63% of staff agree they are adequately prepared for retirement given their current contribution rates. However, a sizable minority of staff (29%) disagree with this viewpoint.

The switch to mandatory contributions is correlated with an increase in the percentage of employees who believe their contribution rates are 'just right.' As shown in Figure 7, the share of faculty that perceived their contribution rates to be just right increased from 64% in 2016 to 76% in 2020. Similarly, the share of staff that perceived their contribution rates to be just right increased from 64% to 69%. A minority of respondents, however, perceive their contribution rates as too high or too low. Nearly one-quarter of faculty and 28% of staff view their contribution rates in 2020 as too low. In addition, 3% of staff (3 respondents) view their contribution rate as too high. These employees are the ones that may be hurt by the change to mandatory contributions.

Figure 7. Perception of Contribution Rates in 2016 and 2020



Behavioral Biases

Behavioral biases could lead to suboptimal contribution rates that are too low. Employees hired before the change to mandatory contributions may have been saving less than they desired, and this change either encouraged or forced them to increase contribution rates to save more optimally. We present summary statistics for evidence of inertia, loss aversion, and present bias.

Two survey questions address a respondent's degree of inertia. Figure 8 shows that 37% of staff respondents and 32% of faculty agree that they procrastinate making financial decisions. However, Figure 9 shows that just 6% of all respondents disagree with the statement "I make a conscious effort to make the best decision on my contribution rate," suggesting that inertia may not be prevalent. Responses by faculty and staff are similar for this question.

Figure 8. Procrastinate Making Financial Decisions

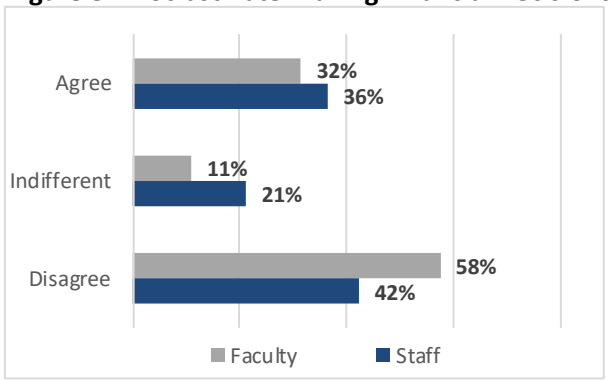
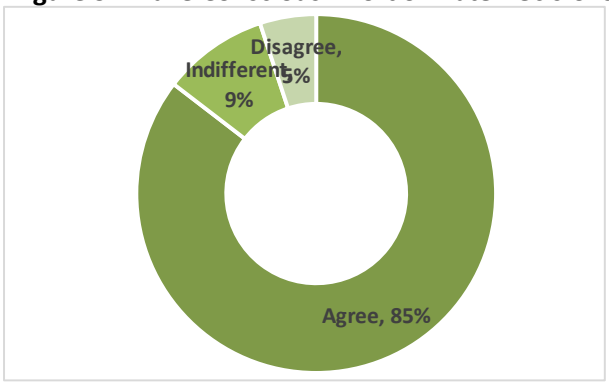


Figure 9. Make Conscious Effort on Rate Decisions



Loss aversion could be contributing to low and suboptimal contribution rates for staff. Two-thirds (107) of all respondents pay attention to the section on their paycheck showing retirement contributions. Of those respondents, as shown in Figure 10, eleven staff (19%) but just two faculty (4%) view the contribution as a reduction from their paycheck rather than an addition to their retirement savings.

Present bias does not seem to be an important bias among the respondents. To calculate effects from present bias, we use the methodology used by Ameriks et al. (2007) where present bias is measured using with the expected-ideal (EI) gap. Respondents are asked about a hypothetical situation in which they receive ten free dinner tickets to any restaurant to use within two years. They first must choose the number they would *ideally* use in each year (Q31). They are then asked how many tickets they actually *expect* to use each year (Q34). The EI gap is computed by subtracting the expected number of tickets used in year 1 by the ideal number of tickets used in year 1. The theory behind this scenario is that those who do have a present bias will choose to use more meal tickets in the first year than their ideal number. A positive EI gap represents a standard problem of overconsumption due to low self-control, and a negative gap corresponds to underconsumption.

When survey respondents were asked about the hypothetical dinner ticket situation, most answered that they would use more tickets in year one rather than year two. However, just 29% stated they would be tempted to use more tickets in year one than initially stated. Moreover, the difference in means of the expected and ideal number of tickets used in year one is less than one whole ticket. This outcome suggests that present bias is not an important reason for suboptimal savings.

Budget Constraints

Figure 11. Increase Contribution Rate if Given Raise

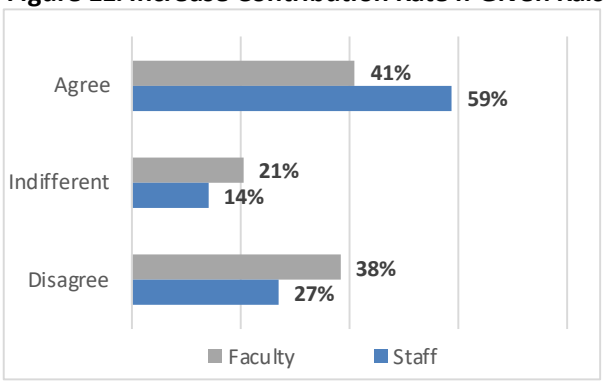
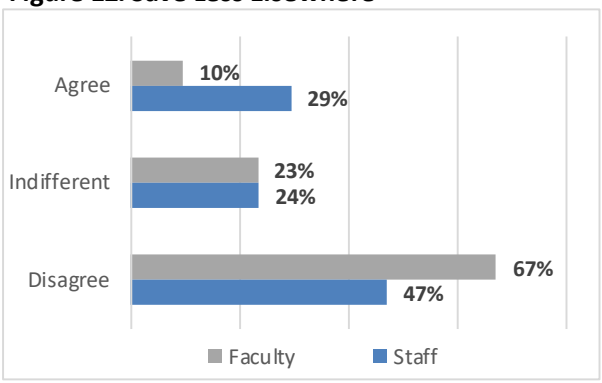


Figure 12. Save Less Elsewhere



Budget constraints prevent many staff from achieving their optimal contribution rates. Figure 11 shows that 41% of faculty answered that they would increase their contribution rate if they received a raise beyond the normal increase for cost of living, but an even greater percentage of staff (59%) would do so. Further, just one faculty member (1%) but 14 staff (17%) contributed the minimum rate of 4% in Fiscal Year 2020. Of the staff respondents, 14 of 15 (93%) would contribute 10% if they could afford to do so.

Two additional survey questions assess the effects from budget constraints. The first asks whether respondents agree with the statement "I offset the adverse effect on my budget from mandatory University of Arkansas contributions by contributing less to my other long-term financial savings accounts (Q19)." Once again, as shown in Figure 12, a larger percentage of staff (29%) than faculty (10%) agree that they save less elsewhere. Finally, Table 1 shows that 51% of staff agree that they have little disposable income after paying for necessities each month, while only 12% of faculty agree with that statement. In sum, staff are more budget constrained than faculty.

Respondents Most Likely Helped and Harmed

In this section, we identify the respondents most likely to be impacted (either helped or harmed) by the switch to mandatory contributions. We then use mean differencing to compare their behavioral biases and budget constraints with respondents less likely to be impacted.

Table 2. Profiles of Employees Most Likely Harmed and Helped

Harmed	Helped
• Contribution rate in 2020 perceived as too high	• Contribution rate increased between year of employment & 2020
• Contribution rate at the minimum 4% in 2020	• Contribution rate in 2020 perceived as just right
• Tight budget constraints	• Strong behavioral biases

Table 2 summarizes the expected employee profiles for each category. Respondents most likely to be harmed by the switch to mandatory contributions perceive their 2020 contribution rate as too high, and their contribution rate in that year is the minimum of 4%. These respondents should exhibit tighter budget constraints than other respondents. Given their awareness that contribution rates are too high, those harmed should be less driven by behavioral biases than other respondents, they should be less prepared for retirement, and less satisfied with the program.

Respondents most likely to be helped are those with strong behavioral biases whose contributions rates increased between their first year of employment[9] and 2020, whether by force or from voluntary decisions. These employees should also perceive their contribution rate as 'just right' in 2020 because the change moved them closer to their optimal rate.[10] We expect these respondents to be more satisfied with the program changes because the increase in the contribution rate, whether forced or voluntary, was perceived positively. Although most of these respondents experienced a reduction in their paychecks, they may still face significant budget constraints because they are more likely to have lower income and contribute at the minimum rate.

For robustness, we also define those helped slightly differently by including only respondents who were employed on or before 2016 (*Helped-2016*). Although this condition reduces the sample nearly in half, these employees were more cognizant of the changes to the retirement plan because they worked—often for many years—under the previous rules, which gives them a different reference point than those hired after the change was in effect.

To conduct mean difference testing, we create a set of variables from the survey, most of which are binary. All variables and definitions are listed in Table 3, but we also describe them here for convenience. The behavioral variables used for mean differencing are as follows. Inertia is proxied by *NoEffort* and *Procrastinate*. *NoEffort* equals one for respondents that either somewhat or extremely disagree that they make a conscious effort each year to make the best decision about their retirement contribution rate, and zero otherwise. *Procrastinate* equals one for respondents who either somewhat or strongly agree that they tend to procrastinate making financial decisions. Loss aversion is measured with *Reduction*, which equals one if respondents

[9] Contribution rates from 2016 are used for those who were employed before the switch to mandatory contributions.
[10] It is also possible that those helped by the change could view their contribution rates as too low if they are budget constrained. Excluding these respondents, however, provides a cleaner identification of behavioral biases and budget constraints.

Table 3. Variable Names and Definitions

Dependent Variables	**Definition**
Harmed	Equals one if the contribution rate in 2020 is too high and is at the minimum of 4%; zero otherwise. (Q14,Q17)
Helped	Equals one if the contribution rate in 2020 is greater than either the contribution rate in 2016 or the first year of employment if it occurred after 2016, and the contribution rate in 2020 is perceived to be just right; zero otherwise. (Q10-Q14,Q17)
Helped-2016	Equals one if the contribution rate in 2020 is greater than the contribution rate in 2016, and the contribution rate in 2020 is perceived to be just right; zero otherwise. (Q10,Q14,Q17)
NotPrepared	Equals one if you somewhat or extremely disagree that at current contribution rate, you will be adequately prepared for retirement, zero otherwise. (Q18)
NotSatisfied	Equals one if you somewhat or extremely disagree that you are satisfied with the mandatory contribution changes to the University's Retirement Plan because they have made you better prepared for retirement, zero otherwise. (Q29)
Explanatory Variables	**Definition**
Income	<$25K=1; $25K-$50K=1; $50K-75K=3; $75K-$100K=4; >$100K=5 (Q6)
NoEffort	Equals one if you somewhat or strongly disagree that I make a conscious effort each year to make the best decision about my contribution rate, zero otherwise. (Q16)
OffsetBudget	Equals one if you extremely or somewhat agree that you offset the adverse effect on your budget from mandatory University of Arkansas contributions by contributing less to other long-term financial savings accounts, zero otherwise. (Q19)
Reduction	Equals one if you think of the section on your paycheck that shows your retirement contributions primarily as a reduction, zero otherwise. (Q23)
Procrastinate	Equals one if you strongly or somewhat agree that you tend to procrastinate making financial decisions, zero otherwise. (Q24)
LittleDispIncome	Equals one if you strongly or somewhat agree that after paying for necessities each month you have very little disposable income, zero otherwise. (Q27)
EIGap	Difference between number of certificates expected to use in Year 1 and the ideal number to use in Year 1. (Q34 less Q31)
Tempted	Equals one if you would be somewhat/strongly tempted to use more certificates in the first year than would be ideal, zero otherwise. (Q32)

think of the section on their paycheck that shows their retirement contributions primarily as a reduction from their paycheck. Respondents only answered this question if they always or frequently pay attention

to the section on their paycheck that shows the retirement contributions. We assume, therefore, that those that do not pay attention to their paycheck also do not view their contributions as a reduction in pay. Finally, present bias is measured with *Tempted* and *EIGAP*. *Tempted* equals one if respondents state they would be somewhat or strongly tempted to use more restaurant certificates in the first year than would be ideal. *EIGAP* is the difference between the expected and ideal number of certificates the respondent would use in the first year. For both variables, higher values signal stronger present bias.

Three budget constraint variables are also used in the mean differencing. *OffsetBudget* equals one if the respondent extremely or somewhat agrees that they offset the adverse effect on their budget from mandatory University of Arkansas contributions by contributing less to other long-term financial savings accounts. *Income* is the respondent's income bracket, which ranges from 1 to 5 where higher values represent higher income. *LittleDispIncome* equals one if the respondent strongly or somewhat agrees that after paying for necessities each month they have little disposable income, zero otherwise.

Finally, we include two variables that assess the respondent's overall perception of the retirement plan. *NotPrepared* equals one if the respondent somewhat or extremely disagrees that at the current contribution rate, they will be adequately prepared for retirement, zero otherwise. *NotSatisfied* equals one if the respondent somewhat or extremely disagrees that they are satisfied with the mandatory contribution changes to the University's Retirement Plan because the changes have made them better prepared for retirement, zero otherwise. (Q29)

Table 4 lists mean differences of key variables between those most likely impacted (harmed or helped) and those less likely impacted by the change to mandatory contributions. We separate staff and faculty in the analysis, but no statistics are reported for faculty that were likely harmed because no faculty fit that profile. The expected signs for the mean differences are listed in the table as well. Differences in means with unexpected signs are shaded, and the differences that are statistically significant at least at the 10% level are in bold font.[11]

Table 4 lists mean differences of key variables between those most likely impacted (harmed or helped) and those less likely impacted by the change to mandatory contributions. We separate staff and faculty in the analysis, but no statistics are reported for faculty that were likely harmed because no faculty fit that profile. The expected signs for the mean differences are listed in the table as well. Differences in

[11] We compute statistical significance of the t-tests conservatively using the pooled method that assumes equal variances of the two groups because the small numbers of observations in the harmed (helped) sample are insufficient to generate reliable variances.

means with unexpected signs are shaded, and the differences that are statistically significant at least at the 10% level are in bold font.[12]

The first row of the table lists the mean change in the contribution rate between 2016 (or first year of employment) and 2020. For those likely harmed, mean contribution rates increased by a statistically insignificant 1.49 percentage points more than for staff less likely harmed. For those more likely helped, contribution rates increased by more than 3.0 percentage points for staff, and at least 1.98 percentage points for faculty relative to those less likely helped, and all four mean differences are statistically significant.

Columns 1 and 2 of Table 4 list the expected signs and mean differences, respectively, for those most likely harmed relative to those not likely to be harmed. Consider the three budget constraint variables: *Income, OffsetBudget, and LittleDispIncome*. We expect the mean income bracket of those harmed to be lower than the mean income bracket of the respondents not harmed, and the mean difference of -0.59 is negative as expected. Similarly, those more likely to be harmed should have little disposable income (positive sign) and offset their budget by saving less elsewhere (positive sign). Indeed, both mean differences in the table are positive, and *OffsetBudget* is also statistically significant. We also expect that these employees will have unfavorable perceptions of the program. Again, the results are consistent with this view. Mean differences in those not prepared for retirement (0.22) and those not satisfied with the program (0.87) are positive, and the latter is statistically significant. On the other hand, we do not expect behavioral biases to be stronger for those that are likely harmed, so the mean differences for the five behavioral bias variables should have negative signs. Table 4, however, shows that the values for two of them, *EIGap* and *Tempted*, are positive and shaded. The bottom portion of the table displays the number of observations in the likely harmed group (2) and the not likely harmed group (83). It also shows that 8 of 10 (80%) variables have the expected signs.

[12] We compute statistical significance of the t-tests conservatively using the pooled method that assumes equal variances of the two groups because the small numbers of observations in the harmed (helped) sample are insufficient to generate reliable variances.

Table 4. Differences in Means of Those Likely Impacted and Those Not Likely Impacted

Mean differences of those most likely to be harmed (helped) less those less likely to be harmed (helped). Shaded cells represent mean differences with unexpected signs. Numbers in bold font represent statistical significance at the 10% level or better.

	Harmed		Helped			Helped-2016	
Variable	Sign	Staff	Sign	Staff	Faculty	Staff	Faculty
Chg in Contribution Rate		**1.49%**		**3.31%**	**1.98%**	**3.06%**	**2.40%**
				Program Perception			
NotPrepared	+	0.22	?	0.18	-0.14	0.22	-0.17
NotSatisfied	+	**0.87**	-	0.11	-0.07	0.11	-0.06
				Behavioral Biases			
NoEffort	-	-0.06	+	0.12	0.11	0.10	0.16
Procrastinate	-	-0.37	+	0.04	0.11	0.06	0.23
Reduction	-	-0.13	+	0.07	-0.03	0.10	-0.04
EIGap	-	1.25	+	-0.09	-0.40	-0.11	-0.90
Tempted	-	0.15	+	0.07	0.23	0.11	0.21
				Budget Constraints			
Income	-	-0.59	-	-0.08	-0.04	-0.31	-0.23
OffsetBudget	+	**0.72**	+	0.00	0.04	0.04	-0.13
LittleDispIncome	+	0.51	+	0.06	0.06	0.07	0.10
No. Harmed/Helped		2		12	7	11	5
No. not Harmed/Helped		83		63	59	38	48
Percent with Expected Sign		80%		78%	78%	78%	67%

Results in columns 4-7 of Table 4 compare mean differences for those likely helped less those not likely helped, and column 3 displays the expected signs. We expect behavioral biases and budget constraints to be stronger for those helped. We also expect these respondents to be satisfied with the program so that the sign on *NotSatisfied* is negative. However, the expected sign for *NotPrepared* is ambiguous because employees may believe they are more prepared for retirement than before the program changes, but they still may be unprepared overall due to budget constraints. For staff likely helped, none of the mean differences are statistically significant. However, four of five behavioral biases (except *EIGap*) have the correct signs, as well as all three budget constraint variables. Interestingly, *NotSatisfied* is positive, indicating that staff most likely helped are not satisfied with the program relative to those less likely helped. In sum, 7 of 9 (78%) of the variables had the expected signs. All these results hold for both definitions of *Helped*. With a few exceptions, results are similar for faculty most likely to be helped. The sign on *Reduction* is unexpectedly negative, suggesting that loss aversion is not an important bias for those faculty. In addition, *NotSatisfied* has the expected negative sign. In all, 7 of 9 (78%) of the variables for *Helped* have the expected signs, and 6 of 9 (67%) have the expected signs for *Helped-2016*, which includes only those that were employed prior to the change to mandatory contributions.

In sum, the analysis in Table 4 reveals that the sample is too small to assess statistical significance of the mean differences.[13] Nevertheless, a high percentage of the mean differences consistently have the expected signs, suggesting that behavioral bias may be an important reason that staff and faculty were helped by the switch to mandatory contributions, and budget constraints may be an important reason that some staff were harmed.

Conclusion

We analyzed survey results of 172 full-time employees at the University of Arkansas to examine the effects from the retirement plan switch to mandatory contributions beginning in Fiscal Year 2017. Minimum required contribution rates increased by one percentage point each year to 5% in Fiscal Year 2022. (The increase from 4% to 5% was delayed one year due to the Covid pandemic.)

We found that 72% of respondents are unaffected by the switch to mandatory contributions because they already contribute 10% or more to their retirement, which is the maximum rate for employee matching. Average contribution rates, however, increased for all full-time employees, and especially for staff where the average contribution rate increased by 1.2 percentage points. In addition, 89% of respondents are either satisfied or indifferent to the changes even though 29% of staff disagree that they are adequately prepared for retirement given their current contribution rates.

We also examined the percentage of employees that were most likely to be harmed or helped by the program changes. Mandatory contributions harm individuals with tight budget constraints who wish to contribute less than the minimum contribution rate. We identified the respondents most likely to be harmed as those that perceive their 2020 contribution rate of 4% (the minimum) as 'too high.' We find that 2.4% of staff may have been harmed by the switch to mandatory contributions. However, logit regression analysis and T-tests of mean differences between those likely harmed and those not likely harmed cannot confirm these results because the sample size is too small.

In contrast, mandatory contributions may help those with strong behavioral biases of inertia, loss aversion, or present bias. Such biases lead individuals to save too little, and mandatory contributions can nudge or force them to save more optimally. Those most likely helped by the change increased their contribution rates at some point between 2016 and 2020 either voluntarily or by force, and they perceived their contribution rates in 2020 as 'just right.' We find that 16% of staff and 11% of faculty may have been helped by the switch to mandatory contributions because it helped them overcome their low savings rates

[13] The mean difference approach analyzes variables one at a time so we cannot determine the relative importance and statistical significance of a particular variable while controlling for the effects from other variables. Multivariate regression analysis overcomes this shortcoming. Unfortunately, our sample size is too small to draw reliable inferences from regressions, so we leave it to future research when a larger survey is undertaken.

resulting from behavioral biases. Again, the power of our statistical tests is too weak to confirm these results.

Our results need to be interpreted with caution because the sample size is too small to conduct statistically reliable tests. Moreover, the respondent sample may not accurately reflect the profiles of university employees, especially faculty profiles. The sample greatly overrepresents employees from the Walton College resulting from our inability to directly solicit responses from employees in other colleges. Consequently, a much larger survey needs to be done across all campuses of the University of Arkansas System to assess with greater statistical confidence the effects on employees from the change to mandatory contributions.

Acknowledgements

This research project builds on the undergraduate Honors Thesis completed by Sarah Brasche in the Spring 2021 semester under the supervision of Dr. Yeager. We thank Katherine Moore in Human Resources for her generous time and effort to gather and provide us aggregate data on employee contribution rates.

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Appendix A. Retirement Plan Survey

Start of Block: Intro

Q0 Sarah Brasche is an undergraduate majoring in Finance. She is conducting her Honors Thesis under the supervision of Professor Tim Yeager (tyeager@uark.edu) in the Finance Department on the effects on retirement savings from recent changes to the University of Arkansas Retirement Plan that required mandatory contributions for all full-time employees. Mandatory contributions began with Fiscal Year 2017 (July 1, 2016 – June 30, 2017) at 1% and have increased by 1% each year. In this current Fiscal Year 2020, the mandatory contribution rate is 4%, and it will cap at 5% in Fiscal Year 2022 (which begins July 1, 2021). It would be so helpful to Sarah if you could take 5 minutes to answer these survey questions. In addition, the research will be used to inform our university community of the effects from these retirement plan changes. The survey must be completed by end of day July 13th.There are no foreseeable risks in taking this survey. If you are uncomfortable with any question, you do not need to answer it. You may stop participating in the survey at any time without penalty (45 CRF 46.116(a)). All responses will be kept confidential to the extent allowed by law and university policy. Should you have questions about the survey itself or how it will be used, you can contact Professor Yeager at 479-575-2992 or tyeager@uark.edu.

You may also contact the University of Arkansas Research Compliance office listed below if you have questions about your rights as a participant or to discuss any concerns about or problems with the research.

Iroshi (Ro) Windwalker, CIP, IRB Coordinator Research Compliance, 109 MLKG Building, Fayetteville, AR 72701 phone 479-575-2208 and fax 479-575-6257

Q1 Are you a full time employee at the University of Arkansas that participates in the University of Arkansas retirement plan? (Answer 'No' if you are participating in the Arkansas Public Employee Retirement System or the Arkansas Teacher Retirement System.)

- ○ Yes (1)
- ○ No (2)

End of Block: Intro

Start of Block: Demographic Questions

Q2 Indicate your gender.

- ○ Male (1)
- ○ Female (2)
- ○ Prefer not to answer (3)

Q3 What is your race or origin? You may select more than one option.

- ☐ Black or African American (2)
- ☐ Asian (3)
- ☐ Hispanic, Latino, or Spanish origin (4)
- ☐ White (5)
- ☐ Other (6)
- ☐ Prefer not to answer (7)

Q4 Indicate your age in years.

_____

Q5 Are you faculty, staff, or administration?

- ○ Faculty (1)
- ○ Staff (2)
- ○ Administration (3)

Q6 In which bracket does your income earned in calendar year 2019 fall?

- ○ < $25,000 (1)
- ○ $25,001 - $50,000 (2)
- ○ $50,001 - $75,000 (3)
- ○ $75,001 - $100,000 (4)
- ○ > $100,000 (5)

Q7 Do you work in the Sam M. Walton College of Business?

- ○ Yes (1)
- ○ No (2)

Q8 When did you begin full-time employment with the University of Arkansas? (If you were full-time and then quit and returned, select the year that you began your most recent employment with the university.)

- ○ Before July 1st 2016 (1)
- ○ Between July 1st 2016 and June 30th 2017 (2)
- ○ Between July 1st 2017 and June 30th 2018 (3)
- ○ Between July 1st 2018 and June 30th 2019 (4)
- ○ After July 1st 2019 (5)

End of Block: Demographic Questions

Start of Block: Yearly Contribution Questions

Q9
For each fiscal year between 2016 and 2020 that you have been employed at the University of Arkansas, you will be asked in these next question(s) to select your total contribution rate to the retirement plan.

To find your contribution rate for a given fiscal year, you can view your past earnings statements on webBasis. After logging on, click **My Pay > Pay Activity**. By searching for any earnings statement between **January** and **June** of a given calendar year, you will be viewing your statement for that **same fiscal year**. (A statement from July through December is for the next fiscal year.) You will see one or two entries in the Deductions section that says something like: TIAA/CREF Mandatory [X%], TIAA/CREF TaxDeferrd [Y%]. (Your statement may reference Fidelity instead.) Add the contribution rates together and that is your contribution rate for the fiscal year.

Display This Question:

If When did you begin full-time employment with the University of Arkansas? (If you were full-time a... = Before July 1st 2016

Q10 Your Fiscal Year 2016 (July 1st 2015 - June 30th 2016) contribution rate (a value of '5', for example, indicates a contribution rate of 5% of your salary). If your contribution is more than 10% please select 11%+.

- ○ 0% (2)
- ○ 1% (3)
- ○ 2% (4)
- ○ 3% (5)
- ○ 4% (6)
- ○ 5% (7)
- ○ 6% (8)
- ○ 7% (9)
- ○ 8% (10)
- ○ 9% (11)
- ○ 10% (12)
- ○ 11%+ (13)

Display This Question:

If When did you begin full-time employment with the University of Arkansas? (If you were full-time a... = Before July 1st 2016

Or When did you begin full-time employment with the University of Arkansas? (If you were full-time a... = Between July 1st 2016 and June 30th 2017

Q11 Your Fiscal Year 2017(July 1st 2016 - June 30th 2017) contribution rate (a value of '5', for example, indicates a contribution rate of 5% of your salary). If your contribution is more than 10% please select 11%+.

- ○ 1% (2)
- ○ 2% (3)
- ○ 3% (4)
- ○ 4% (5)
- ○ 5% (6)
- ○ 6% (7)
- ○ 7% (8)
- ○ 8% (9)
- ○ 9% (10)
- ○ 10% (11)
- ○ 11%+ (12)

Display This Question:

If When did you begin full-time employment with the University of Arkansas? (If you were full-time a... = Before July 1st 2016

Or When did you begin full-time employment with the University of Arkansas? (If you were full-time a... = Between July 1st 2016 and June 30th 2017

Or When did you begin full-time employment with the University of Arkansas? (If you were full-time a... = Between July 1st 2017 and June 30th 2018

Q12 Your Fiscal Year 2018 (July 1st 2017 - June 30th 2018) contribution rate (a value of '5', for example indicates a contribution rate of 5% of your salary). If your contribution is more than 10% please select 11%+.

- ○ 2% (3)
- ○ 3% (4)
- ○ 4% (5)
- ○ 5% (6)
- ○ 6% (7)
- ○ 7% (8)
- ○ 8% (9)
- ○ 9% (10)
- ○ 10% (11)
- ○ 11%+ (12)

Display This Question:

If When did you begin full-time employment with the University of Arkansas? (If you were full-time a... = Before July 1st 2016

Or When did you begin full-time employment with the University of Arkansas? (If you were full-time a... = Between July 1st 2016 and June 30th 2017

Or When did you begin full-time employment with the University of Arkansas? (If you were full-time a... = Between July 1st 2017 and June 30th 2018

Or When did you begin full-time employment with the University of Arkansas? (If you were full-time a... = Between July 1st 2018 and June 30th 2019

Q13 Your Fiscal Year 2019 (July 1st 2018 - June 30th 2019) contribution rate (a value of '5', for example, indicates a contribution rate of 5% of your salary). If your contribution is more than 10% please select 11%+.

- ○ 3% (4)
- ○ 4% (5)
- ○ 5% (6)
- ○ 6% (7)
- ○ 7% (8)
- ○ 8% (9)
- ○ 9% (10)
- ○ 10% (11)
- ○ 11%+ (12)

Display This Question:

If When did you begin full-time employment with the University of Arkansas? (If you were full-time a... = Before July 1st 2016

Or When did you begin full-time employment with the University of Arkansas? (If you were full-time a... = Between July 1st 2016 and June 30th 2017

Or When did you begin full-time employment with the University of Arkansas? (If you were full-time a... = Between July 1st 2017 and June 30th 2018

Or When did you begin full-time employment with the University of Arkansas? (If you were full-time a... = Between July 1st 2018 and June 30th 2019

Or When did you begin full-time employment with the University of Arkansas? (If you were full-time a... = After July 1st 2019

Q14 Your Fiscal Year 2020 (July 1st 2019 - June 30th 2020) contribution rate (a value of '5', for example, indicates a contribution rate of 5% of your salary). If your contribution is more than 10% please select 11%+.

- 4% (4)
- 5% (5)
- 6% (6)
- 7% (7)
- 8% (8)
- 9% (10)
- 10% (11)
- 11%+ (12)

End of Block: Yearly Contribution Questions

Start of Block: Contribution Policy Questions

Display This Question:

If When did you begin full-time employment with the University of Arkansas? (If you were full-time a... = Before July 1st 2016

Q15 The University began mandatory contributions of 1% for full-time employees in Fiscal Year 2017 (Beginning July 1st 2016.). In your opinion, was your contribution rate in the previous Fiscal Year 2016 (July 1st 2015 to June 30th 2016) too high, too low, or just right?

- Too high (1)
- Too low (2)
- Just right (3)

Q16 I make a conscious effort each year to make the best decision about my retirement contribution rate.

- ○ Extremely agree (1)
- ○ Somewhat agree (2)
- ○ Neither agree nor disagree (3)
- ○ Somewhat disagree (4)
- ○ Extremely disagree (5)

Q17 In your opinion, is your contribution rate in the Fiscal Year 2020 (July 1st 2019 through June 30th 2020) too high, too low, or just right?

- ○ Too high (1)
- ○ Too low (2)
- ○ Just right (3)

Q18 At my current contribution rate, I believe I will be adequately prepared for retirement.

- ○ Extremely agree (1)
- ○ Somewhat agree (2)
- ○ Neither agree nor disagree (3)
- ○ Somewhat disagree (4)
- ○ Extremely disagree (5)

Q19 I offset the adverse effect on my budget from mandatory University of Arkansas contributions by contributing less to my other long-term financial savings accounts.

- ○ Extremely agree (1)
- ○ Somewhat agree (2)
- ○ Neither agree nor disagree (3)
- ○ Somewhat disagree (4)
- ○ Extremely disagree (5)

Display This Question:

If Your Fiscal Year 2020 (July 1st 2019 - June 30th 2020) contribution rate (a value of '5', for exa... = 4%

Q20 Are you planning to increase your contribution rate in the Fiscal Year 2021 (July 1st 2020 to June 30th 2021)?

- ○ Definitely yes (1)
- ○ Probably yes (2)
- ○ Might or might not (3)
- ○ Probably not (4)
- ○ Definitely not (5)

Q21 If you were to get an increase in salary beyond the expected raise for cost of living (e.g. from a promotion), would you contribute a larger percent to retirement?

- Definitely yes (1)
- Probably yes (2)
- Might or might not (3)
- Probably not (4)
- Definitely not (5)

Q22 Do you pay attention to the section on your paycheck that shows your retirement contributions?

- Always (5)
- Frequently (1)
- Sometimes (2)
- Rarely (3)
- Never (4)

Display This Question:

If Do you pay attention to the section on your paycheck that shows your retirement contributions? = Always

Or Do you pay attention to the section on your paycheck that shows your retirement contributions? = Frequently

Q23 Do you think of the section on your paycheck that shows your retirement contributions primarily as an addition to your retirement savings account or a reduction from your paycheck?

- An addition (1)
- I am indifferent (2)
- A reduction (3)

End of Block: Contribution Policy Questions

Start of Block: Likert Scale Questions

Q24 I tend to procrastinate making financial decisions.

- Strongly agree (1)
- Somewhat agree (2)
- Neither agree nor disagree (3)
- Somewhat disagree (4)
- Strongly disagree (5)

Display This Question:

If Your Fiscal Year 2020 (July 1st 2019 - June 30th 2020) contribution rate (a value of '5', for exa... = 4%

Q25 When my mandatory contribution rate increases it has a negative effect on my budget and lifestyle.

- Strongly agree (1)
- Somewhat agree (2)
- Neither agree nor disagree (3)
- Somewhat disagree (4)
- Strongly disagree (5)

Display This Question:

If Your Fiscal Year 2020 (July 1st 2019 - June 30th 2020) contribution rate (a value of '5', for exa... = 4%

Q26 If I could afford to contribute 10% in order to receive the highest retirement matchings from the university, I would.

- Definitely yes (1)
- Probably yes (2)
- Might or might not (3)
- Probably no (4)
- Definitely no (5)

Q27 After paying for necessities each month I have very little disposable income.

- Strongly agree (1)
- Somewhat agree (2)
- Neither agree nor disagree (3)
- Somewhat disagree (4)
- Strongly disagree (5)

Display This Question:

If Your Fiscal Year 2020 (July 1st 2019 - June 30th 2020) contribution rate (a value of '5', for exa... = 4%

Q28 The adverse effect on my budget has gotten easier to accept as the mandatory contribution rate has risen each fiscal year.

- Strongly agree (1)
- Somewhat agree (2)
- Neither agree nor disagree (3)
- Somewhat disagree (4)
- Strongly disagree (5)

Q29 I am satisfied with the mandatory contribution changes to the University's Retirement Plan because they have made me better prepared for retirement.

- ○ Strongly agree (1)
- ○ Somewhat agree (2)
- ○ Neither agree nor disagree (3)
- ○ Somewhat disagree (4)
- ○ Strongly disagree (5)

End of Block: Likert Scale Questions

Start of Block: Meal Tickets Questions

Q30 Now we will present you with a hypothetical situation. Please answer the following questions after careful consideration of this situation.

Situation: Suppose you win ten certificates, each of which can be used (once) to receive a "dream restaurant night." On each such night, you and a companion will get the best table and an unlimited budget for food and drink at a restaurant of your choosing. There will be no cost to you: all payments, including gratuities, come as part of the prize. The certificates are available for immediate use, starting tonight, and there is an absolute guarantee that they will be honored by any restaurant you select if they are used within a two-year window. If they are not used up within this two-year period, however, any that remain are valueless.

Q31 From your current perspective, how many of the ten certificates would you ideally like to use in year 1 (as opposed to year 2)?

0	1	2	3	4	5	6	7	8	9	10
Year 1 ()										

Q32 Some people might be tempted to depart from their ideal allocation. Which of the following best describes you?

- ○ I would be strongly/somewhat tempted to keep more certificates for use in the second year than would be ideal. (1)
- ○ I would have no temptation in either direction. (2)
- ○ I would be somewhat/strongly tempted to use more certificates in the first year than would be ideal. (3)

Q33 If you were to give in to your temptation, how many certificates do you think you would use in year 1 (as opposed to year 2)?

	0	1	2	3	4	5	6	7	8	9	10
Year 1 ()											

Q34 Based on your most accurate forecast of how you think you would actually behave, how many of the nights would you end up using in year 1 (as opposed to year 2)?

	0	1	2	3	4	5	6	7	8	9	10
Year 1 ()											

End of Block: Meal Tickets Questions

Appendix B. Estimate of Average Staff Salary and Increase in Retirement Contributions

Table B.1 shows the assumptions made to estimate the average staff salary and increase in retirement contributions at the University of Arkansas in FY2020. Each survey respondent identified the income bracket they fell into in FY2020, and we used those values to compute a representative salary (usually the mid-point) for each bucket, shown in the *Estimated Avg. Income ($)* column. We then weighted each estimated salary by the number of staff in that income bracket and summed across all buckets to arrive at the weighted salary of $52,072 (e.g. the 25K-50K bracket is weighted by multiplying $37,500 x 53/90). Finally, the increase in retirement income is the estimated change in staff dollar contributions to retirement income in FY 2020 relative to what the contribution would have been without the change to mandatory contributions. The value of $625 is computed by multiplying the average staff salary of $52,072 by the average change in the retirement contribution rate of 1.2%. The matched value of $1,250 accounts for the university match of 1.2%.

Table B.1. Estimated Increase in Retirement Contributions in 2020

Income Bracket	Estimated Avg. Income ($)	Number of Staff	Weighted Salary ($)	Increase in Retirement Income ($)
<25K	22,000	2	484	6
25K-50K	37,500	53	21,841	262
50K-75K	62,500	19	13,049	157
75K-100K	87,500	13	12,500	150
>100K	110,000	4	4,835	58
Sum:		91	52,709	633
Matched:				1,266

Faculty Highlights

Jamie I. Baum, PhD, has mentored over 30 undergraduate students since joining the University of Arkansas in November of 2011. Dr. Baum serves as the Director for the Center of Human Nutrition and as a faculty member in the food science department. Baum received her bachelor's degree in Dietetics (2000) and her PhD in Nutritional Sciences (2004) from the University of Illinois at Urbana-Champaign. Baum briefly worked in the food industry as a nutrition scientist in the Netherlands before returning to academia.

Baum teaches multiple courses related to food science and food health and currently has eight undergraduate students working in her lab, at the Don Tyson Center for Agricultural Sciences, examining the importance of proteins in the human body. Baum's research group studies dietary proteins using a molecule-to-man approach. Baum and her students investigate the proteins we eat, whether it be animal or plant protein, and how they impact overall muscle mass.

Baum's lab also compares different patterns of protein intake in order to identify what is most beneficial to the health of humans.

Baum's research aims to show that healthy muscles create a healthy life, and that proteins play a vital role in muscle growth and keeping muscle healthy. Baum opines that being informed about what you're eating and planning your diet is essential.

"As plant-based and other sustainable forms of protein become more popular in the media, it is important to find combinations of proteins that maintain a healthy diet while also having a good carbon footprint," Baum remarked.

In addition to studying the effect of protein on muscle mass, Baum's research group has been reinventing protein intake through the utilization of 3D food-printing. Using "food-ink", Baum and her students craft and print personalized protein diets for those who need help absorbing nutrients into their body. This is targeted mainly towards elderly individuals because our bodies become less able to collect nutrients as we age.

Baum emphasized that engaging in hypothesis-driven research is incredibly important, even if you're not researching in science-related areas.

"Anyone can benefit from understanding the scientific method and being able to use those skills in the future when looking at information from other sources," Baum stated. "It helps develop critical thinking skills, and makes students learn to ask their own questions. It also teaches them about failure, because 99% of research is picking yourself back up and learning what to fix for next time."

Baum disclosed that her research wouldn't be possible without her undergraduate mentees. When Baum isn't in her lab, she enjoys cooking for friends and spending time with her son.

Paul Adams, PhD, has mentored over 60 undergraduate students since joining the University of Arkansas in January of 2007 as a faculty member in the Chemistry and Biochemistry department. Currently, four undergraduates are working in Dr. Adams's lab. Adams is originally from Baton Rouge, Louisiana. He received his bachelor degree in biochemistry from the Louisiana State University and his PhD in biophysical chemistry from Case Western Reserve University.

Adams and his students use a variety of biochemical techniques to characterize interactions between proteins that have roles in the onset of diseases, such as cancer. Adams and his students have determined that there is great significance in the specific movements of molecules within a cell in relation to interactions with certain drugs and other entities. Adams said that he and his students hope to obtain information that may potentially lead to the design of novel therapeutic approaches against cancer.

"We're hoping that studying these general interactions could lend itself to a broader understanding of approaching drug design in the future," Adams remarked.

Adams explained that undergraduate research is essential for students' growth and provides them an opportunity to think critically about their work instead of just looking for the right answer. He added that undergraduate research is pivotal to broadening a student's awareness of tools and skills they will use beyond the traditional classroom setting.

"I think that exposure is very important. Looking at my own experience, when I was younger, I had no idea that I would be pursuing a career in science like I am today. I just hadn't been exposed to that before," Adams said. Before coming to the University of Arkansas, Adams was a postdoctoral scientist at Cornell University in New York, a research-focused opportunity that he frequently encourages both his undergraduate and graduate students to consider.

Adams is married to Dr. Stephanie Adams, Director of Faculty Development in the Provosts' Office at the UofA, and they have 3 children. He enjoys spending time with his family, saying that he often attends his children's athletic competitions at school. Adams is an active member of Omega Psi Phi Fraternity, Inc., a fraternity he joined when he was in college, and continues to participate in social and community projects as a member of the fraternity.

Interviews conducted by Sophia Nourani

OUR awards Summer Research Grants to Non-Honors Students

Last year, the Office of Undergraduate Research (OUR) awarded Summer Research Grants to 25 non-honors undergraduate students. The Inquiry team met with few of these Summer grant recipients to reflect on their experience with their mentors and the program.

The Summer Undergraduate Research Grant Program was established in order to support experimental projects from a wide range of disciplines at the University of Arkansas. These projects are facilitated through student-faculty collaboration. OUR expects to continue funding non-honors undergraduate students to pursue research.

Elizabeth Hays, a senior biology major from Springhill, Kansas, is studying the effect(s) of construction on the native box turtles on Markham Hill. Hays is working under Dr. J.D. Wilson, whose lab was contacted by the real-estate company that purchased Markham to safely move the turtles to a new home range. Hays said the field materials required to track and monitor these turtles are extremely expensive.

Hays, along with all of the other undergraduate students participating in the program, stressed the technology and other equipment necessary to execute their projects would have been out of their price range if not for receiving the grant.

Many of the students found their mentors through doing online research and did not know them before participating in the grant program. Alexia Lo, a senior biochemistry major from Gentry, Arkansas, is one of these students. Lo says that her mentor, Dr. Paul Adams, became like a father to her over their time working together.

"My grandfather passed away with colon cancer. I remember having a conversation with Dr. Adams... he had something on his webpage that said what got him to become a research professor because his mother passed away with cancer. And so me and him, we had a long conversation about cancer and losing someone that we love to it. So that's what inspired me. I decided I want to do something that would impact the community, you know, help out."

Dr. Adams' lab uses a variety of biochemical techniques to characterize interactions between proteins that have roles in the onset of diseases, such as cancer.

Besides growing strong relationships with professionals in their desired career fields, all of the students conveyed gratitude for the resume-building experience, and advocated that any student interested in undergraduate research should pursue it.

"The one motto that I've always been reminded of during my three semesters of working in the laboratory is to think critically and 'work smarter, not harder'", Lo remarked. "Aside from critical thinking, research also aids in bettering skills needed in the real world-like communication, writing, being able to interpret and analyze data, and a lot more."

Interviews conducted by Sophia Nourani

Honors Corner

The past year has been a banner year for honors students engaged in undergraduate research. The Covid pandemic took a toll on students' progress, as time in labs was curtailed, museums and archives closed, and in-person interviews and studies ended or forced online. However, with the aid of their mentors, students have persevered and adapted their research methods to our new normal.

Across three grant deadlines this year, the Honors College has awarded 160 Honors College Research Grants, providing $514,00 in funding to students and $240,000 to their mentors. Students are engaged in grant-funded research across all six colleges. This year students also started presenting research at in-person conferences for the first time since before the pandemic. Over two dozen honors students won a Conference/Workshop Travel Grant to present research at regional, national, and even international conferences.

Research experiences can be wildly different depending on a student's course of study and their specific interests. However, regardless of what topic a student chooses to pursue, research can have a tremendous impact on their undergraduate experience and their prospects after graduation. Some students' research will help propel them into graduate or professional schools, while others plan to leverage the skills they developed through research as leverage on the job market. The experiences of two students, one in Biology and the other in English Creative Writing, showcase the breadth of research and what it offers students:

Davin Means, a Biology major headed to medical school in the Fall, is researching glioblastomas and the differentiation between IDH mutant and IDH wildtype cells. Davin's research has been challenging but also rewarding! He writes of his experience, "The Honors College Research Grant has transformed me into a more patient, detail-oriented person, and under the guidance of Dr. Rajaram, my critical thinking skills in regard to experimental design have greatly improved." Davin has developed many diverse skills from research: "I have learned that carefully planned, methodically organized, extensively detailed, and consistently documented experimentation minimizes the risk of confounding variables, and I have come to understand the importance of scientific rigor and transparency in reducing experimental bias…Furthermore, in working with…peers in the lab, I've become acquainted with the synergy, communication, and cooperation necessary for the advancement of science and research."

Davin Means, bringing glioblastoma cells into focus using the Bruker Ultima Investigator inverted multiphoton microscope.

Olivia Schapp, a senior English Creative Writing major who wrote a collection of personal essays for her thesis, found that though her research wasn't "traditional," it will still give her an advantage as she pursues her writing career. "My thesis has not only honed my craft as a writer, helped me grow interpersonally, and given me a network of faculty and resources," Olivia said, "but it will also leave me with polished works for my portfolio upon my graduation in Spring of 2022. I have been fortunate to have several nonfiction essays published in local journals, and am excited that my thesis will add another distinction to my CV to help me advance my writing career." Olivia used her Honors College Research Grant as a personal stipend, freeing up more time to dedicate to her writing.

Olivia Schaap "assumes the (writing) position" to work on her series of personal essays.

No matter your major, honors research is a rewarding endeavor and sets you apart from your peers!

Interested in starting your honors research?

- Find out what is required for research by your college. Go to the honors website for your academic college and read the information there regarding the honors thesis. These links are also available at honorshub.uark.edu, under the Research tab.
- Collect information and examples of research in your major. Visit honorsstories.uark.edu to read dozens of blogs written by students about their research. Talk to your professors or graduate assistants about what research typically looks like in your discipline.
- Consider what topics in your field interest you. Remember, you don't need a specific research question at this point! Just start narrowing down your interests.
- Look into what faculty are researching. You will ask a faculty member to be your mentor whose research expertise aligns with your interests. Visit the departmental website for your major and/or closely related fields. Google the name of your department and "UARK" to find the departmental website. Then go to the faculty directory and click on their names to see their profiles.
- Seek out additional help! The Research tab on honorshub.uark.edu has more information on finding a research topic and a mentor. Keep an eye out for workshops on these topics and more! You can also schedule a 1:1 meeting with the Director of Grants and Research Innovation, Chelsea Hodge, on UASuccess for additional guidance.

National Undergraduate Week Poster Presentation Competition

In April 2022, the University of Arkansas celebrated National Undergraduate Research Week with its own week-long celebration of student research conducted on our campus. This week, hosted by the Honors College, Office of Undergraduate Research, and University Libraries, included a Research Poster Competition, that exhibited the breadth of research/creative projects undertaken by undergraduate students at the university. Over 50 honors and non-honors students entered the competition. The winners in the eight research categories are listed below.

Art/Design & Humanities

First Place
Emily Snyder
Hometown: Bentonville, AR
Major(s): History, Latino and Latin American Studies
"The Political Power of Museums: A Case Study on the Museum of Spanish Colonial Art"
Mentor: Shawn Austin

Second Place
Kaleigh Alwood
Hometown: Centerton, AR
Major(s): Music Education, Music Theory
"Analysis of Robert Schumann's "Fantasy Pieces for Clarinet and Piano", opus 73, for a Greater Understanding of a Standard in Western Classical Solo Repertory"
Mentor: Nophachai Cholthitchanta

Third Place
Daniella Ruiz Cantu
Hometown: Bentonville, AR
Major(s): Political Science
"Black Occularity, the White Gaze, and Color-Blindness in Shonda Rhimes' Bridgerton"
Mentor: Lisa Corrigan

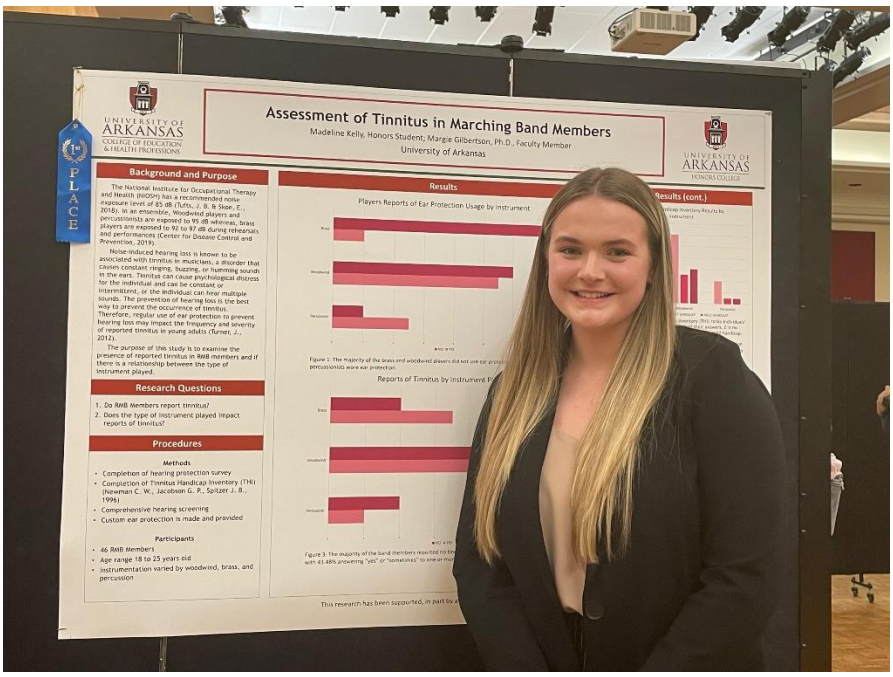
Engineering

First Place
Fah Sysavanh
Hometown: Springdale, AR
Major(s): Biomedical Engineering
"The Interaction of Angiotensin I and II on Calcified Aortic Valve Cells"
Mentor: Kartik Balachandran

Second Place
Katherine Skiles
Hometown: Baton Rouge, LA
Major(s) Biological Engineering
"Representativeness Evaluation of the Delta-Flux Network for Assessing Rice Landscapes in the Mid-South"
Mentor: Benjamin Runkle

Third Place
John Sooter
Hometown: Bentonville, AR
Major(s): Industrial Engineering
“Developing a carbon inclusive pricing model for time constrained last mile delivery services”
Mentor: Chase Rainwater

Health Group 1

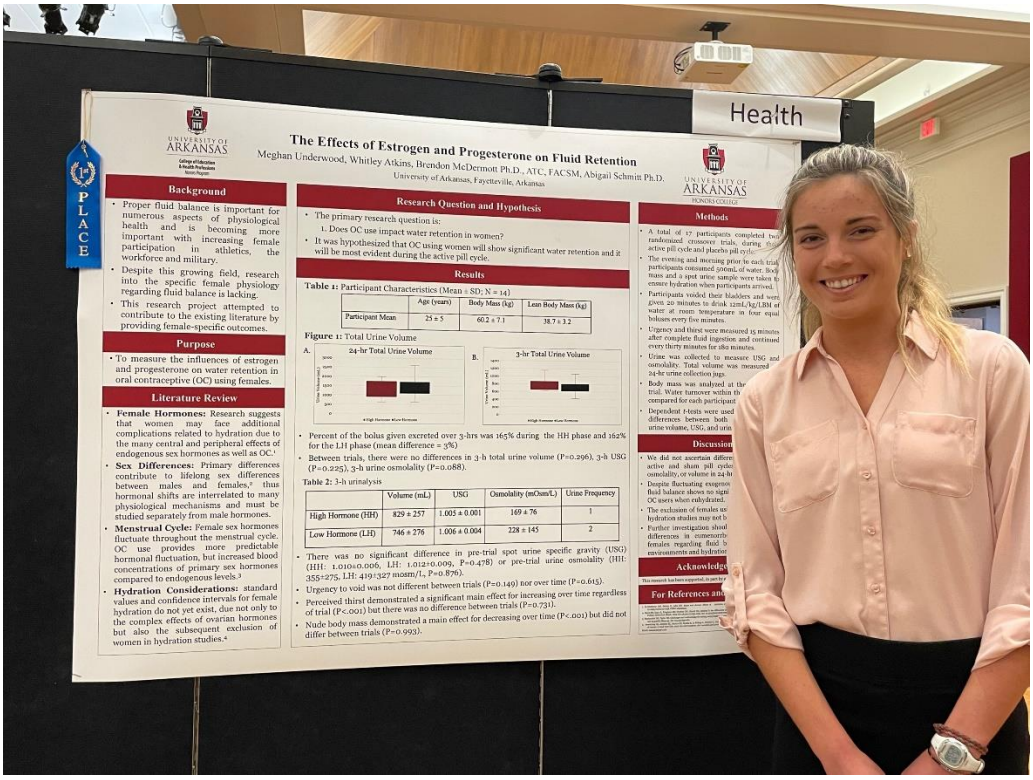


First Place
Madeline Kelly
Hometown: Plano, TX
Major(s): Communication Sciences and Disorders
“Assessment of Tinnitus in Marching Band Members”
Mentor: Margie Gilbertson

Second Place
Savannah Ellis (O’Fallon, MO; Biology, Psychology) and Sarah Aly (Fayetteville, AR; Biomedical Engineering)
“The Effect on Mental, Physical, and Social Health as a Result of the Return to In-Person Classes”
Mentor: Samantha Robinson

Third Place
Alric Fernandes
Hometown: Bentonville, AR
Major(s): Chemistry, Biology
“Robust Geographically Weighted Regression to Explore Regional Differences in Tobacco Use Determinants”
Mentor: Samantha Robinson

Health Group 2



First Place
Meghan Underwood
Hometown: Memphis, TX
Major(s): Exercise Science
“Effects of Estrogen and Progesterone on Fluid Retention and Perceived Thirst”
Mentor: Brendon McDermott

Second Place
Haley Stanton
Hometown: Mabelvale, AR
Major(s): Animal Science
“Prevalence of Ehrlichia and Rickettsia Species in Ticks in Arkansas State Parks”
Mentor: Ashley Dowling

Third Place
Brittany Martin
Hometown: Dover, AR
Major(s): Kinesiology, Exercise Science
“Correlation Between Circulating Inflammatory Biomarkers, DOMS, and Self-rated Function in Lean and Obese Populations After a Heavy Lifting Protocol”
Mentor: Brendon McDermott

Natural Science Group 1

First Place

Nathan Rives
Hometown: Fayetteville, AR
Major(s): Biology
"Type I Antifreeze Protein in Polar Fish as a Model to Study Convergent and New Gene Evolution"
Mentor: Xuan Zhuang

Second Place
Miller Bacon
Hometown: Little Rock, AR
Major(s): Biochemistry, History
"Amine Enhancement of Cyanoacrylate Fuming of Fingerprints"
Mentor: Wesley Stites

Third Place
Alexia Lo
Hometown: Gentry, AR
Major(s): Biochemistry
"Characterization of a Ras-Related Protein in the Presence and Absence of a Small Molecule Inhibitor"
Mentor: Paul Adams

Natural Science Group 2

First Place
Dominic Dharwadker
Hometown: Fayetteville, AR
Major(s): Biochemistry, French
"Regulation of vacuolar H+ translocating pyrophosphatase (V-PPase) impacts sucrose formation and cytosolic pH during germination in rice"
Mentor: Vibha Srivastava

Second Place
Ashley Lieber
Hometown: Wichita, KS
Major(s): Physics
"Modeling the Variability of the Sun's Total Solar Irradiance through Supervised Machine Learning Techniques"
Mentor: Julia Kennefick

Third Place
Ethan Peters
Hometown: Fayetteville, AR
Major(s): Biochemistry, Spanish
"Design of a stable variant of FGF1-FGF2 dimer with potent cell proliferation activity"
Mentor: Suresh Kumar

Social Science Group 1

First Place
Hannah Frala
Hometown: Fayetteville, AR
Major(s): Psychology

"Using Social Media to Regulate Emotions is Associated with Psychopathology"
Mentor: Jennifer Veilleux

Second Place
Danielle Shaver
Hometown: Germantown, TN
Major(s): Psychology, Social Work
"It's Not You, It's Me: Contextualizing Relationship Conflict, Self-Criticism, and Emotion Regulation"
Mentor: Jennifer Veilleux

Third Place
Brynn Schuetter
Hometown: Conway, AR
Major(s): Psychology, Criminology, Sociology
"The Effects Identification Procedures Have on Eyewitness Identification"
Mentor: James Lampinen

Social Science Group 2

First Place
Aryn Blumenberg
Hometown: Conway, AR
Major(s): Food Science
"Consumer Preferences for Lab Grown Meat: The Effect of Information on Consumer Choice"
Mentor: Nathan Kemper

Second Place
Ryan Harra
Hometown: Olathe, KS
Major(s): Psychology
"The effectiveness of peer to peer Mentoring"
Mentor: Ivan Vargas

Third Place
Trinity Walker
Hometown: Fayetteville, AR
Major(s): Psychology, Spanish
"Theory of Mind: temporary super power or coincidence?"
Mentor: Bill Levine