

*33<sup>rd</sup> Electric Vehicle Symposium (EVS33)  
Portland, Oregon, June 14 - 17, 2020*

# **Stochastic Revenue Analysis of Electric Vehicle Participation in Californian Demand Response Markets**

Oliver Garnett, M.Sc.<sup>1</sup>, Huai Jiang, M.Sc.<sup>2</sup>

<sup>1</sup>*Energy and Environmental Economics, Inc. (E3). 44 Montgomery St., Suite 1500, San Francisco, CA 94104,*

<sup>1</sup>*oliver@ethree.com*

<sup>2</sup>*huai@ethree.com*

---

## **Summary**

The authors estimated the potential revenue from an EV aggregation participating in the California Independent System Operator (CAISO) Proxy Demand Response (PDR) market through managed charging under a range of scenarios. Annual driving and charging profiles were developed for a sample of drivers using stochastic Markov-Chain Monte Carlo (MCMC) techniques. Charging was then optimized against a forecasted PDR price stream to simulate an EV aggregators bidding EV battery capacity into the CAISO PDR market to earn revenues. Results illustrate a broad range of revenues could be realized, although, under a base case (i.e. an unmanaged charging baseline, medium-distance commuter, operating in the day-ahead market, with a 250 mile BEV) revenues at the workplace were on average only 8 \$/EV-year and if participating in PDR at home, 31 \$/EV-year. Under certain conditions this revenue could be as high as 237 \$/EV-year but depends strongly on the commute distance, baseline charging profile, real-time or day-ahead market participation, and the level of charging at home.

*Keywords: Proxy Demand Response, Vehicle Grid Integration (VGI), electric vehicle supply equipment (EVSE), BEV (battery electric vehicle)*

---

## **1 Introduction**

Decarbonization of the transport sector is a crucial policy goal for many nations aiming to reduce Greenhouse Gas emissions. A rapid decline in the cost of Lithium-ion battery technology in recent years has made electrifying transport an attractive option for decarbonization and put electric vehicles (EVs) on a path to become the dominant form of road transport by 2050 [1]. Since a single EV can consume almost half as much energy annually as an entire home, EV adoption at such scale will have a significant impact on electricity grids. There is therefore a growing need to find smarter ways to manage EV charging load to minimize the burden on electric utilities and unlock the vast potential EVs could have in helping balance the grid. One approach is to shift the timing of EV charging in response to a price signal, known as smart charging, V1G, or managed charging.

The theoretical value that a managed charging service provides for utilities and the grid has been demonstrated in various studies using marginal cost value streams and different charging patterns [2, 3, 4]. However, many barriers need to be overcome before this theoretical value could be captured by vehicle drivers, EV charging aggregators, vehicle manufacturers, or other stakeholders needed to promote and deliver managed charging services. One such barrier is that few programs or products exist today that are accessible to an EV aggregation resource and from which viable business models can be created to incentivize managed charging. In addition, little is known about what revenues an EV aggregation might expect to see from real products and programs that are currently available and accessible.

One potential product that could be accessible to EVs through managed charging is the California Independent System Operator (CAISO) Proxy Demand Response (PDR) program. The PDR product was developed by CAISO to increase participation of demand response resources in ISO Energy and Ancillary Service markets. The program allows demand response providers to bid load curtailment into day-ahead and real-time wholesale energy markets as well as day-ahead and real-time non-spin and spin markets [5].

A key challenge for EV aggregators wishing to participate in ISO markets through PDR is predicting how much EV battery capacity is available to participate on an hourly basis which in turn depends on driving behaviour, charging patterns, charging access and many other factors. Studies that have investigated how EV aggregators might optimize charging have generally focused more on the role of a scheduling coordinator dispatching an EV aggregation alongside other resources and have only a coarse representation of the behavioural dynamics of drivers [6, 7]. Some researchers provide a more stochastic representation of driving behaviour but do not combine this with a revenue analysis for EV aggregators [8]. This work attempts to capture behavioural diversity of driving in a rigorous way, investigate how it aligns with wholesale market prices, and then establish what impact this has on aggregator revenues.

The main objective of this paper is to explore how an aggregation of managed EVs might participate in the wholesale real-time and day-ahead energy markets through PDR and we estimate the revenues that could be expected under such a scenario. A stochastic markov-chain monte carlo technique is used to generate driving schedules representative of the driving population to account for variation in driving behavior. These profiles are then used to simulate EV charging loads that are managed through a linear optimization tool.

## 2 Methods

The analysis involved three main steps, as outlined in Figure 1. First, driving profiles are created from 2017 National Household Transportation Survey data [9] and the Markov-Chain Monte Carlo technique. The resulting driving profiles are then used to simulate EV driving and charging using E3's load simulation tool, RESHAPE. Finally, charging sessions are managed by an EV aggregator using the RESTORE model which dispatches behind the meter distributed energy resources through linear optimization. The potential for participation of EVs in the PDR market both at home and at the workplace is investigated.

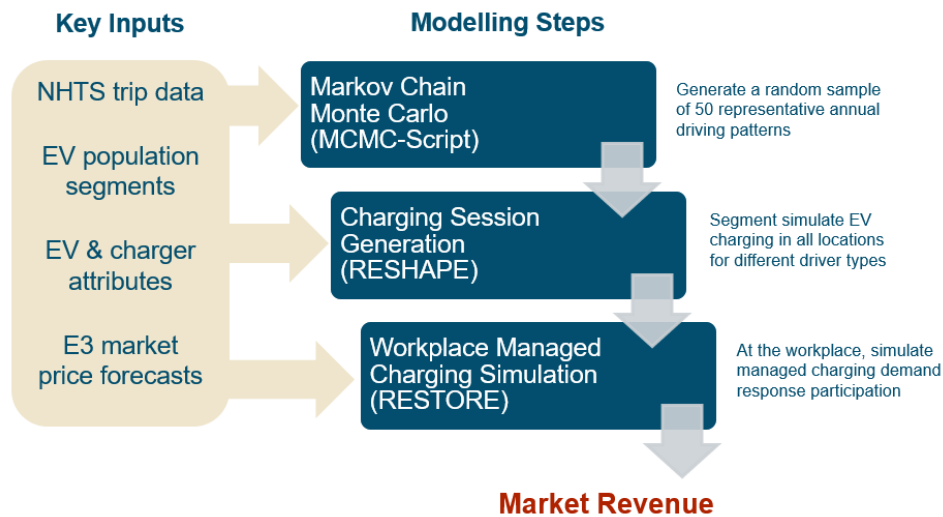


Figure 1: Method for estimating potential revenue from an EV participation in the California ISO Proxy Demand Response (PDR) market

The methodology section first lays out the various scenarios that were selected for simulation and then describes the steps for generating driving profiles, generating charging sessions, and how charging was managed for the EV aggregation.

## 2.1 Cases

To identify the full range of potential revenue from an EV aggregation participating in the CAISO PDR market various cases were developed combining different parameters:

- Vehicle types: 4 vehicle types were tested, a long- and short-range Battery Electric Vehicle (BEV) and a long and short-range Plug-in Hybrid Electric Vehicle (PHEV).
- Commute distances: three samples of drivers were used to generate driving profiles: Drivers in the top 50<sup>th</sup> percentile for commute distance, drivers in the bottom 50<sup>th</sup> percentile for commute distance and drivers from all commute distances. This gave driving profiles representing drivers with long, short, and medium commute distances.
- Market product: The PDR market product gives participants access to CAISO's wholesale energy markets to bid in as load curtailment. Another, yet to be released product known as PDR Load Shift Resource (PDR-LSR) is also explored, this product is the same as PDR but also allows participants to bid into the market as demand when wholesale energy prices are negative.
- Market type: Real-time and day-ahead market price forecasts were developed to explore both markets for the PDR and PDR-LSR products
- Baseline charging profiles: To participate in PDR through managed charging a baseline charging profile must first be established. During a PDR call event an EV stops charging when it is scheduled to charge. The load reduction from the baseline charging profile determines how much capacity can be bid into the market. Two different baselines were explored; an unmanaged charging baseline where vehicles charge to their full state of charge immediately on arrival at a location with access to charging, and a Time of Use (TOU) tariff baseline in which charging is concentrated as much as possible outside of TOU peak hours.
- Location: Simulations were carried out where EVs could participate in PDR when at home or at the workplace.

Permutations of the above parameters formed the modelling cases for simulation with each case being modelled using a sample of 50 drivers over a year. The cases were simulated for 2020, 2023, and 2025 to understand how

revenues may evolve over time. The base case selected was a medium distance commuter, with a BEV that has 250 miles of range, an unmanaged baseline charging profile, participating in the Day Ahead PDR market.

## 2.2 Driving Trip Generation

Annual driving patterns were generated for 50 drivers for each commute distance type (long, medium, and short). The National Household Travel Survey dataset was used to gather trip data on a large sample of Californian drivers. This dataset was filtered and cleaned to represent commuter drivers of personal light duty vehicles. The trip data was then converted to an annual driving profile using the Markov Chain Monte Carlo (MCMC) simulation method following the steps shown in Figure 2.

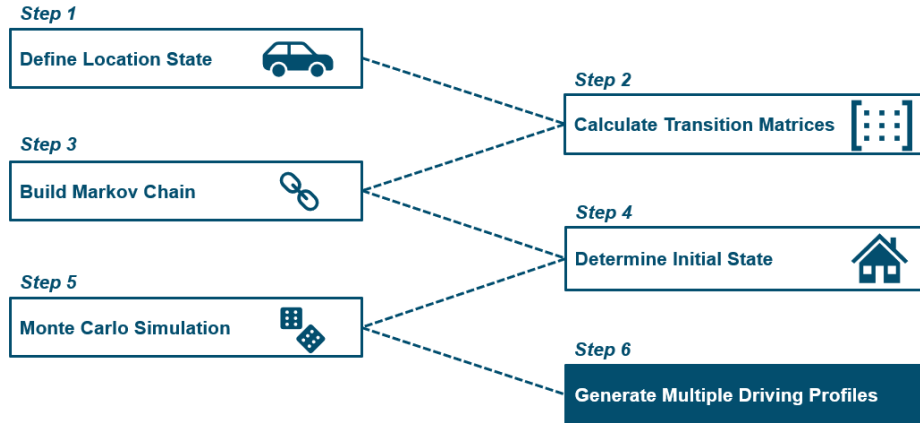


Figure 2: MCMC method for simulating driving profiles

The MCMC method defines five location states for the driving profile, including home, workplace, public place with access to chargers, public place without access to chargers, and driving/on the road. For each 15-min time window, a vehicle is tagged with a single state indicator. The probability of transitioning from one state to the other is calculated for every 15-minute window using the historical NHTS dataset. This forms a set of probabilities known as transition matrices for a weekday and a weekend. The state in each time window is stochastically generated through Monte-Carlo simulation to construct annual driving profiles. The initial state is randomly chosen based on the state distribution in the first-time window (e.g. 12:00 am of a weekday). The process is iterated many times to create a set of driving patterns that fully represent the driving behaviour of the entire population. For more detail on implementation of the MCMC methodology see [10, 11].

## 2.3 Charging session generation and managed charging simulations

To generate charging sessions the annual driving profiles were input into E3’s RESHAPE load generation tool which segments the driving population based on charging access and vehicle type, generating normalized loads for each segment. Charging session metrics such as arrival time, departure time, energy consumed during session were then managed using the RESTORE dispatch optimization tool using the PDR price streams.

To develop a market price forecast for the PDR and PDR-LSR market products in both real time and day ahead markets, E3 generated future wholesale energy market price forecasts in DA market for California using Energy Exemplar’s AURORA model and E3’s own projections of future generation mixes and electricity market dynamics. The volatility between California SP-15 and NP-15 DA market and RT market was captured from historical data and applied on top of DA price forecast to derive RT price.

As described in CAISO documentation [12], PDR resources are only dispatched when the energy market prices are above the net-benefits threshold NBT price and are therefore zero in all hours below this. A forecast for the

NBT was generated based on E3’s gas price forecasts and historical NBT data. E3 assumes the EV aggregator bids into the PDR market at the NBT price.

To manage charging the RESTORE model would simply shift charging to the lowest priced hours subject to various constraints. A target for the state of charge of the battery on departure is one key constraint that is set by the driver on arrival at site. This was set to 100% to be conservative and ensure minimal range anxiety is experienced by participants. If the vehicle was not present long enough for the vehicle to reach 100% SOC then no charge management could occur. Finally, for simplicity no constraint was added for charging infrastructure meaning that all EV’s at home and work always had a dedicated charger and did not have to share plugs.

### 3 Results

E3’s analysis found a very broad range of EV revenue potential from PDR and PDR-LSR with annual revenues ranging from 2 – 237 \$/EV-year. Under the base case, the sample average revenue potential was \$8/EV-year at the workplace and 31 \$/EV-year at home across the 50 drivers in the sample. It was found that commute distance, the baseline charging profile, the level of home charging, and the market type (day-ahead vs real-time) all had a strong influence on revenue potential. While vehicle type (BEV or PHEV), vehicle range (provided it was above 50 miles), and market product (PDR vs PDR-LSR) had limited or negligible impact on revenue. The revenues also did not vary much annually between 2020 and 2025.

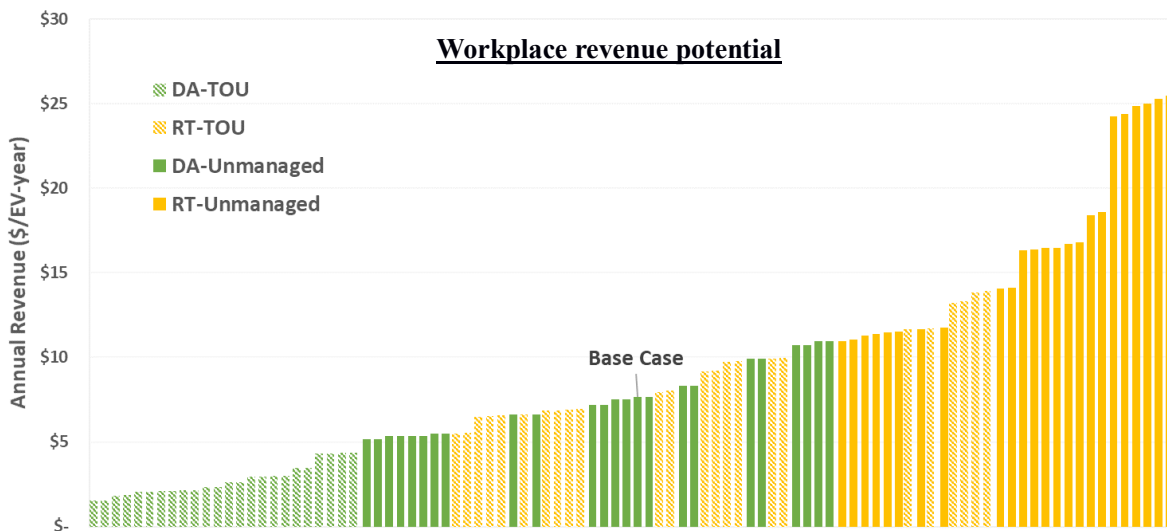


Figure 3: Distribution of revenue from the CAISO PDR product from **workplace** managed charging. Note each bar represents the mean annual revenue of the 50-driver sample.

Poor alignment of PDR market prices with workplace charging hours and the lower volume of energy charged were the primary reasons for revenue at work being around 4 times less than revenue at home. Since energy market prices tend to peak in the late afternoon and are generally lower during morning and early afternoon there were much fewer opportunities for the EVs to be managed for PDR at work compared to home. The amount of energy charged at home also tends to be higher because workplace charging tends to only replenish commute driving whereas home charging is used to replenish other trips as well. This study assumed every vehicle at work

had a dedicated charger plug but in reality, vehicles would likely have to share plugs which would limit the flexibility to manage charging and therefore further reduce revenues at work compared to home.

A much wider distribution of revenues can be seen in for PDR participation at home as shown in Figure 4, where sample averages were as high as 237 \$/EV-year for RT market participation with drivers that have an unmanaged baseline charging profile, a long commute, and level 2 charging at home.

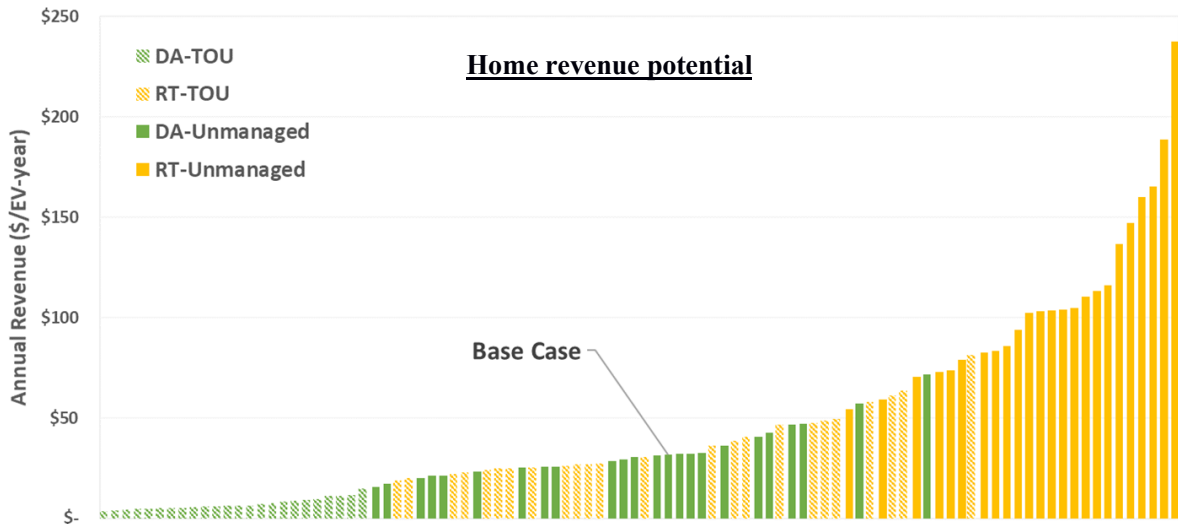


Figure 4: Distribution of revenue from the CAISO PDR product from managed charging at **home**. Note each bar represents the mean annual revenue of the 50-driver sample.

Figure 3 and Figure 4 show the large difference between the day-ahead PDR market (green) and real-time PDR market (yellow) cases. Revenues were significantly higher if EVs were participating in the real-time market which is expected due to the much higher price volatility. Since RESTORE is a linear optimization tool with perfect foresight actual revenues obtainable from the RT market are expected to be lower however this simulation still provides a useful upper bound.

The underlying charging pattern used to generate the baseline from which demand response is measured played a significant role in determining revenue. Using managed charging as a demand response resource means an EV can only make revenue in a particular hour if under the baseline scenario the EV is charging in that hour and can therefore stop charging to show a reduction in load. Unmanaged charging profiles resulted in PDR baselines that could unlock much higher revenue compared to if the EV was already varying its charging profile in response to TOU tariff peaks. This impact is much stronger at home than work because TOU peaks tend to also coincide with high price PDR hours. Under a TOU baseline charging tends to be shifted to low price PDR hours resulting in significant revenue loss. It should be noted that generally the TOU peak price differential was significantly larger than the PDR market price making it much more lucrative overall for EVs to focus on responding to TOU peaks than PDR market signals.

Commute distance was found to influence revenue potential at work significantly and at home more moderately. Drivers with longer commutes have greater charging needs and therefore offer more energy shifting potential and higher PDR revenue potential. Work revenues are more sensitive to commute distance because the commute is the only driving that tends to be replenished by charging at work, whereas home charging is used to replenish non-commute trips as well.

Finally, the distribution of revenue within the sample of 50 drivers was often broad with the highest annual revenue seen for a single driver being 308 \$/EV-year suggesting the driving pattern also has a strong influence

on revenue. However, the nature of the MCMC method used for this study makes it difficult to further segment the driver population based on driving pattern characteristics without explicitly generating driving profiles to target a particular characteristic. For example, drivers that show a pattern of arriving at work early or leaving work late might allow us to identify high value drivers based on these traits, but this is beyond the scope of this study.

## 4 Conclusions

Previous studies have shown that managed charging could offer a significant revenue opportunity from wholesale markets in California. This analysis took a much deeper look at the revenue opportunity using a currently available CAISO market product and analysed a range of parameters that vary across the EV driver population such as EV type, charging access, commute distance, and baseline charging behaviour. E3's analysis demonstrates that for a medium commuter, driving a BEV with 250 miles of range, who is not on a Time-of-use tariff at work or home, and participates in the day-ahead PDR market, an average of \$8/EV-year could be expected at the workplace and 31 \$/EV-year at home. However, under the right conditions upper estimates for these values could be as high as 25 \$/EV-year at work and 237 \$/EV-year at home. Capturing the higher revenue estimates requires drivers not being on a TOU tariff at home or work, participating in the real-time PDR market, having a long commute to work, and having access to level 2 charging at home. Other products and programs such as utility demand response could provide much higher revenues and should be explored in future work to support business model development and foster the deployment of VGI technology.

## Acknowledgments

The authors would like to thank Mr. Eric Cutter and Mr. Robert Shaw for their contributions to this study.

## References

- [1] B. N. E. Finance, "When Will EVs Be Cheaper Than Conventional Vehicles?," March 2018. [Online]. Available: <https://www.bnef.com/core/insights/18271>.
- [2] Energy & Environmental Economics and EPRI, "Distribution System Constrained Vehicle-to-Grid Services for Improved Grid Stability and Reliability," 2019.
- [3] J. J. T. M. a. K. W. J. Zhang, "Value to the Grid from Managed Charging based on California's High Renewables Study," *IEEE Transactions on Power Systems*, vol. 34, no. 2, pp. 831-840, 2018.
- [4] J. Coignard, S. Saxena, J. Greenblatt and D. Wang, "Clean vehicles as an enabler for a clean electricity grid," *Environmental Research Letters*, vol. 13, no. 5, 2018.
- [5] California Independent System Operator, "Proxy Demand Resource (PDR) & Reliability Demand Response Resource (RDRR) Participation Overview," [Online]. Available: [https://www.caiso.com/Documents/PDR\\_RDRRParticipationOverviewPresentation.pdf](https://www.caiso.com/Documents/PDR_RDRRParticipationOverviewPresentation.pdf). [Accessed 2020].
- [6] S. Sharma, P. Jain, R. Bhakar and P. Prasanta Gupta, "Time of Use Price based Vehicle to Grid Scheduling of Electric Vehicle Aggregator for Improved Market Operations," *IEEE*, pp. 1114-1119, 2018.

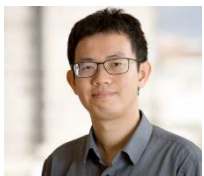
- [7] V. Sankaranarayanan and R. Sowmya, “An Optimal Model for Electric Vehicle Battery Charging and Discharging Scheduling Strategy,” *2019 National Power Electronics Conference (NPEC)*, pp. 1-6, 2019.
- [8] M. Ebrahim Hajibadi, H. Ghanbari and M. Samadi, “Comprehensive Review of Literature on the Statistical Behaviors of Electric Vehicle Aggregators (EVAs): Modelling the Pdf of Power Production of EVA Using Classic CLT,” *The 24th Electrical Power Distribution Conference*, pp. 72-79, 2019.
- [9] Federal Highway Administration, “National Household Travel Survey 2017,” 2018. [Online]. Available: <https://nhts.ornl.gov/>.
- [10] F. Soares, P. Rocha Almeida and J. A. P. Lopes, “A stochastic model to simulate electric vehicles motion and quantify the energy required from the grid,” *17th Power Systems Computation Conference*, 2011.
- [11] M. O’Mahony and J. Brady, “Modelling charging profiles of electric vehicles based on real-world,” *Sustainable Cities and Society*, vol. 26, pp. 203-216, 2016.
- [12] California Independent System Operator, “Demand Response Net Benefits Test,” 2011. [Online]. Available: <http://www.caiso.com/informed/Pages/StakeholderProcesses/CompletedClosedStakeholderInitiatives/DemandResponseNetBenefitsTest.aspx>.

## Authors



Oliver Garnett focuses on the challenges and benefits of effectively integrating distributed energy resources (DER) into the electricity system. His recent projects include quantifying the grid and ratepayer benefits of electric vehicles (EVs) and charging infrastructure, demand response program analysis, microgrid tariff design, and valuation of energy storage.

**Education:** MSc, economics and policy of energy and the environment, University College London; MSci, chemistry, Imperial College London



Huai Jiang works mainly on both distributed energy resources (DER) with the focus on electric vehicles (EV) and resource planning practice areas at E3. His recent projects include evaluating vehicle grid integration benefits under demand response programs, developing tools for calculating benefits and costs for integrated demand side management (IDSM), and analysis of high renewable resource penetrations at both the bulk and distribution levels to help utilities, state agencies, and grid operators prepare for a decarbonized future.

**Education:** MS, environmental policy and economics, and MSE, applied math and statistics, Johns Hopkins University; BS, chemistry, Peking University, China