Berkeley Economic Review

| Content

Professor Interviews

Research Paper(s)

Cover

| Peer Review Board

| Policies

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| From The Editors' Desk

Dear BER Reader,

On behalf of the 68 staff members of *Berkeley Economic Review's* eight departments and executive team, we are proud to present the Spring 2020 volume of our namesake journal, *Berkeley Economic Review.*

In conjunction with our printed semesterly magazine, *Equilibrium*, *Berkeley Economic Review* aims to provide a discourse on diverse, thoughtful, and important economic issues that we face in our time. Our namesake journal receives submissions from all around the world, and we are tasked with a difficult yet humbling decision to select and publish papers that we consider to be outstanding and innovative. In doing so, we firmly believe that *Berkeley Economic Review* helps provide a platform for honoring and showcasing excellent undergraduate work.

As the world grapples with the effects of COVID-19 and other difficult issues of our time, we hope that the content of our journal can present you a moment of distraction from the chaos. Inside, you will find the different perspectives that economics can help illuminate, as well as an excellent undergraduate research paper.

Without further ado, we present to you the 9th volume of *Berkeley Economic Review*.

Best,
Yechan Shin & Vinay Maruri
Editors-In-Chief
Berkeley Economic Review

Professor Andres Rodriguez-Clare

Interviewed by ***Grace Jang***

Andres Rodriguez-Clare is a Professor of Economics at UC Berkeley, Director of the Trade Research Programme at the International Growth Centre, and a Research Associate at the National Bureau of Economic Research. His research interests include industrial policy, multinational production and technology diffusion, economic growth, and the gains from trade.
Interviewer: Good morning, Professor. I would like to start by asking about your background and the experiences that influenced your interest in economics.

Rodriguez-Clare: I like math, and I also like philosophy and politics. I thought economics would be a very interesting way of doing something that was at an intersection of these interests. Also, my father is an economist in Costa Rica; he got his PhD from Berkeley. When I grew up, I would see the books that he had, and I would take a look at those books and talk to him about it. I grew up in an environment where economics was very present. My father was also involved in many conversations about policy at the level of economy, and that had an impact on me. I thought those conversations were very stimulating, and I wanted to better understand those policy aspects myself.

Interviewer: What led you to decide that you want to pursue a PhD in economics and become a professor as opposed to other career options in economics?

Rodriguez-Clare: I studied economics at the University of Costa Rica. That was in the 80's. The university actually was quite good. They had very good professors who had done their PhD in the US and who are now in important positions. For example, I studied public finance from a person who was the Minister of Finance when he was teaching. There were other examples like that. I learned international microeconomics from somebody who was the head of one of the major banks in Costa Rica. We were taught monetary economics from somebody who, just a few years later, was a president of the central bank. So there was this amazing combination of people who were solid as economists and had done their studies in the best places in the US, and now in the positions of important influence in Costa Rica. They were taking their time off their schedule to teach at the university. So that was very stimulating. I decided I wanted to continue studying economics, and a way to do that was to get a PhD.

At that point, professor wasn't something that crossed my mind. In Costa Rica, full-time professors weren't well-paid; usually we had people who worked at banks or owned some business while engaging in policy discussion and teaching at the University of Costa Rica. I thought that's what I would do; the role models I had were people doing that. But once I came to the US to get my PhD at Stanford, I saw academia was quite nice. You could continue doing research and teach. So by the time I was finishing my PhD, I was doing well, and they suggested that I go on the job market and get a job in academia. That happened, and I did that for a few years.

Interviewer: Do you have any plan on returning to Costa Rica?
Rodriguez-Clare: No, for now, I don't have plans like that. I already did that. When I finished my PhD at Stanford, I went to Costa Rica for a year, then I came back to Chicago for three years, then I went back to Costa Rica for five years. These two trips were because my father entered politics – he ran for president – and I helped him with his campaign and presidential work. I learned a lot and enjoyed it, but I doubt that I would ever have a condition again to do it in such a good way. In this case my father was the president, so I had perfect access to the government, and there were no issues that usually arise when you want to enter into politics like competition and people wanting to influence the president. I don't think that it would be as nice again. Plus, I'm happy here teaching and doing research. So for now I'm not thinking of going back.

Interviewer: You have taught at Harvard, MIT, University of Chicago, and Penn State University before coming to UC Berkeley. Based on your experience, what are some differences and/or similarities between the economics departments of these universities?

Rodriguez-Clare: At Harvard and MIT, I didn't get to expe rience them in the same way as the others because I was visiting. At that time, I was living in Washington D.C., where I was working at the Inter-American Development Bank, and I would fly back and forth between the D.C. and Boston weekly. So I don't think I can really compare. For Chicago, I think it's a great, very intense environment. It's known for people being very passionate about economics and the power of market and incentives. I was just coming out of my PhD, and I learned a lot in a place with great economists. At Penn State, I had a tenure and was more established. I enjoyed that too. I had a very good group of colleagues in a small town, where I could focus on academics and research. Then I moved here. I've been here for nine years, and this has been the best place so far. I love my colleagues and have very good students. Also, Berkeley is a great place to live.

Interviewer: A common view is that UC Berkeley economics is more non-conventional than places like University of Chicago. What do you think about this?

Rodriguez-Clare: Yes, I would say that's right. I think Berkeley puts more emphasis on deviations from rational expectations as in behavioral economics; inequality; and empirical approach to economics, as in all the works on randomized controlled trials. And then we have all the work that's being done in labor economics and public finance. I didn't see as much of this at Chicago, or at least in the 90's when I was there. I think that's one of the strengths of Berkeley. It's a very open place, where there is less adherence to tradition and more openness to things that may contradict the way we thought about economics in the past, and more following the data and what the empirics is telling us.

Interviewer: What led you to choose international trade as your subfield?

Rodriguez-Clare: That goes back to my studies of economics in the University of Costa Rica in the 80's. This was a time when Costa Rica was moving from policy of import substitution and protectionism. That system went along with high rates of growth in the 60's, but that was a time when most countries in the world were growing pretty fast. Then in the 70's we had the oil crisis and recessions in many places, and then big crises in the beginning of the 80's in Central America. Costa Rica then started discussing the need to open up to trade. There were many interesting debates on whether we needed to do it at all and how fast to do it. So that time was very stimulating intellectually because there were very different views on what the country should be doing, and a lot of that was about trade policy. And Costa Rica being a small country, trade policy was very critical to its performance because Costa Rica relies a lot more on trade than, let's say, the US, which is a large country and doesn't rely as much on trade. So I thought I wanted to understand how international trade affects a country's possibility to grow and how efficient the economy would be and what the implications would be for distribution and inequality.

Interviewer: Going further from that, you taught us various theories of international trade. Which one do you think best fits the reality?

Rodriguez-Clare: I think they all have something to tell us. The way to think about it is, the reality is complex, and we can understand it in parts. I like to think about the Heckscher-Ohlin model telling us something about how international trade affects factor prices and skill premium. And I like to think about the Offshoring model also affecting skill premium and employment opportunities for workers of different skills. I like to use the Specific Factors model to think about how people with very specialized skills will be positively or negatively affected by trade, depending on whether their sector grows or shrinks. So different models tell us different things, but they are all capturing different slices of the reality.

Interviewer: Could you tell us about the research work you've done in the past and research areas you're currently looking into? How are you thinking of collecting your data?

Rodriguez-Clare: I've been working on the ways of understanding how big the gains are from trade. More recently, I've been working on understanding how those overall gains are distributed across different groups of people, with a particular application to the way the China shock has affected different groups. It has overall benefits, but it also has costs, especially for groups employed in sectors that are competing with imports from China. I have a paper that puts together a general framework that can help us compute these distributional implications.

In recent years, I've been thinking about the effects of all that on employment. The work I was describing before focuses on welfare and real wages. Within the tradition of international trade, labor supply is perfectly inelastic, so all the effects of trade are happening through prices—price of labor and price of goods. But more recent research tries to see how those shocks affect employment, both because people may decide to drop out of the labor force and because unemployment rate increases. During and before the Great Recession, there was a time of higher unemployment, and there is a question of how much of that can be traced back to the China shock.

Most of my work is theoretical, so I usually use widely available data, like those produced by the Bureau of Economic Analysis or the Census. My research doesn't need to go out and generate my own data.

Professor Emmanuel Saez

Interviewed by ***Savr Kumar***

Recently, I had the opportunity to interview world-renowned professor and economist Emmanuel Saez whose myriad accomplishments speak for themself. Professor Saez, the Director of the Center for Equitable Growth at UC Berkeley, recently co-authored a book with fellow professor Gabriel Zucman, 'The Triumph of Injustice,' his research focusing mainly on taxation, distribution and inequality. His proposal of a wealth tax – a tax on the wealth of the 0.01 percent – seeks to correct the imbalance in the current system of taxation today. Professor Saez's research suggests that for the first time ever, billionaires possibly pay taxes at a lower rate than the rest of American society. This idea has found great interest in US presidential campaigns, especially considering that Professor Saez advised Senator Warren on her wealth tax proposal.

Interviewer: Many people do not fully understand the wealth tax and think that it is implausible to implement, for example, for reasons such as that it has not worked well in Europe. I know that you have answered this question. During this election, what do you think have been some of the most prominent/ incorrect misconceptions of the wealth tax?

Saez: Those who are skeptical of the wealth tax, present two main arguments. The first one is that it is never going to work- the rich are always going to find ways to hide their wealth. The second is that it is going to hurt the economy because people who are thinking of developing businesses, becoming wealthy, will be less motivated. These arguments are not consistent however, because if the rich are going to be able to avoid the wealth tax you are not going to be less motivated to earn money.

I think that the perception that the wealth tax won't work based on the experiences of other countries is also prevalent, but what people misunderstand is that whether it works in the US is going to depend, very crucially, on the design and the enforcement of the tax. The enforcement of the tax was very poor in Europe. In the US it would be a lot stronger. For example, in Europe it was easy to avoid the wealth tax by moving to another country which didn't have the wealth tax. In the US, the wealth tax will be based on citizenship so even if you move abroad you will be liable for the wealth tax. To avoid the wealth tax, you must renounce your citizenship. Even then you may be charged with the tax.

Interviewer: You mentioned that since 1980, the incomes of the bottom half of the US population have essentially stagnated in real terms. What do you think may happen to the economy and society if wealth inequality continues to progress in the way that it does- If democracies cannot successfully elect leaders who enact reforms to reduce inequality?

Saez: I don't see how it could be sustainable for society to experience economic growth at the macro level. It shuts away a large chunk of the population from economic growth. If it continues like this, it will generate discontent. Those who don't experience economic growth are not going to be happy with the system and they are going to look for alternate solutions and the way that this is playing out in the US is that the candidates that are nominated are anti-establishment, preferring to do things very differently. On the right you have this new populism, authoritarianism of Trump. On the left you have candidates proposing really radical solutions such as Bernie Sanders and Elizabeth Warren to address the issue of inequality. So, I think that in 2020 the options for the US election are what you would call an extreme right-wing and a radical left-wing candidate running for the president's office.

Interviewer: You have said that the wealth tax represents a possible buffer against economic shock. Some economists have said the next great recession may be due. What is your opinion on this correlation and how inequality is related to volatility?

Saez: Having some wealth is essentially a buffer against economic shock. The problem is that a very large fraction of the US population doesn't have that buffer because they have essentially zero wealth. Inequality makes the cost of volatility higher. When there is a downturn a large portion of the population without wealth will suffer real economic hardships because they cannot absorb the shock.

Whether more inequality makes the economy more volatile in the first place is not actually clear, but I would say that inequality generates volatility of the political nature, causing swaying from right to left, and I think that this, in turn, can generate economic volatility.

Interviewer: You likened inequality deniers to climate change deniers- do you think that the inequality problem is among the most serious problems facing the world today? What are other economic problems of similar magnitude that also need to be addressed such as the trade war?

Saez: I think that the two biggest problems for the sustainability of society are, one, climate change and the second is the ratio of how resources are distributed, which Is the inequality problem. When you have an economy which grows equitably, or all income groups progress at the same rate, the issue of inequality is not really seen as much of a problem. After World War 2 for instance, the growth of economies was strong and equitable. Now we have changed to a regime where gross inequality is a very big issue.

The big issue I would also mention today is the great inequality across countries. Large portions of the (global) population live in poverty. There are some countries which have not completed the transition to being developed economies. There have been a lot of problems of poverty in countries such as China and India, for instance.

Interviewer: The effective tax rate of the 400 richest Americans was 23 percent last year. The top 400 taxpayers in 2014 gave something like 10 billion, relative to the wealth they have of 2.5 trillion. Why do you think that action has not already been taken? How can the social/ ideological influence of billionaires be overcome?

Saez: Yes, I would say that we don't know very much about how much billionaires are paying in tax – we don't know very much yet.

We were the first really to come up with an estimation about how much we think the billionaires are paying in taxes relative to their true economic income and we had the shocking finding that they may be paying less in taxes than the rest of the population. So, before starting to solve the problem, the first step is figuring out the nature of the problem. So, I want to emphasize that we need more studies to fully understand the nature of the problem. Then policymakers and economists can figure out what the appropriate solutions to the problem are.

Secondly, billionaires are powerful. They can use their wealth to influence society. They can do it through spending money, influencing think tanks, nonprofit organizations. They can also give money directly to campaigns, even sponsor new candidates or existing ones. So, how we can reduce the influence of very big money is an important question. The wealth tax takes the wealth of billionaires year after year and reduces their power; it is the most direct way to reduce wealth concentration. There are, however, other policies that are also worth looking into that promote regulation of the influence of money in politics.

Interviewer: Many are at pains to distinguish income inequality and poverty. Do you see this distinction as important? If so, do you think that one problem may be more pressing than the other (especially in the developing world) and how do you think that the wealth tax would affect the latter?

Saez: So, I think wealth inequality and poverty are related but they are not the same thing. Poverty- you can think about it in terms of whether people possess the minimum level of resources to sustain themselves. That is how the World Bank defines poverty at the global level. It is the amount that they think is the bare minimum amount to survive. That issue is an issue of development. Now we still have poverty worldwide because there are several countries, multiple in Africa, for instance, that have not developed yet (to the extent of other countries). There is no such absolute poverty in the United

States, where poverty is defined as living on 2 dollars a day, or less. Even though the risk of starvation is lower in the US, the problem of income inequality remains very relevant because humans are social beings and therefore, they evaluate their own situation relative to others in their group. No matter how rich we are – we are much much richer in the US today than we were a hundred years ago- there is still a feeling of deprivation when you're perpetually less than others in your country. That's why the issue of inequality, I think, will always be with us, even if all countries are rich and at a good level of economic development.

Interviewer: So that's relative poverty that you're describing?

Saez: Correct. In the US, it's a problem of relative poverty, but what is relative poverty? It is exactly the same as inequality.

Interviewer: Do you think that other countries with major wealth inequality may follow suit after the US employs such a wealth tax?

Saez: Yes, I think that the US has the possibility of reinventing tax progressivity for the 21st century and one important effect would be cracking down on very large accumulated fortunes. So, a wealth tax that is well enforced and therefore is successful – we do think that the US can make that demonstration: it could have big impacts on countries in the world that have seen a lot of wealth concentration. I think an analogy is when the US, in the early part of the twentieth century, was the country that created a very progressive income tax. It is possible that tax progressivity in the 21st century will be increased with (the advent of) a progressive wealth tax.

Interviewer: You mentioned a 'plutocratic drift' – which is a feedback loop where more income and wealth at the top are leading to policy outcomes that are more favorable to [those at the top]. Those at the top have a grip on consensus in Washington. Do you think that backlash within the government and big business could prevent the wealth tax from being passed/ running effectively?

Saez: I think that is what we're hearing now. Now that there may be a possible wealth tax there is backlash from some Republicans but also from some moderate Democrats who are tied to the establishment and are influenced by wealthy donors who truly don't like the idea of a wealth tax. This difference in opinion is generating a debate about whether it should be created.

Interviewer: How do you think that these top earning individuals/ billionaires may react to the tax?

Saez: Generally, billionaires don't prefer the wealth tax because it is a hefty tax which they would have to pay. Today, some on the right have been vehemently against the wealth tax. Others, like Bill Gates, have been more open to it- if it is a moderate wealth tax- as they can see why they would be paying more.

Professor David Roland-Holst

Interviewed by ***Ani Banerjee***

David Roland-Holst is an Adjunct Professor affiliated with the Department of Agricultural & Resource Economics and the Department of Economics at University of California, Berkeley. He is the Managing Director and Principal of the Center for Economics, Resources, and Innovation. His research focuses on environmental economics and topics such as climate change, agriculture, and biofuels.

Interviewer: What drew you initially to economics? Why agriculture/resource economics specifically, and why developing countries?

Roland-Holst: First of all, I had a sort of formative experience as a teenager when I met an economist named Kenneth Golding, who's kind of a combination philosopher-economist and he made a really deep impression on me personally, even though at the time I was just a high schooler. Then I went into university and I actually majored first in mathematics because I was mostly interested in that at the time, but I took a double major in economics partly because of Golding's influence. When I finished I came to Cal and got my Ph.D. here and I was in Math-Econ at the time because that was a good combination of economic theory and mathematics. As I progressed through my graduate days I became more interested in application, particularly in developing economies. My dad had been a diplomat so I lived in a lot of developing economies as a kid, so I decided I wanted to shift away from pure theory and work more in applied theory, particularly in areas where there was a really obvious need for economic progress. That got me into development and finally, when I got my degree at Cal in 1985, it was economic development. After graduating, I went to a teaching institution -- Mills College, which is right here in the Bay and had a very distinct advantage of being in the environment I kind of prefer. I kept doing that work, basically doing policy research for developing economies. I made a transition to Berkeley again in 2003, so I've been here about 17 years. I combined motivation for teaching —I love to teach—with my research interest. I've worked in 40 different developing countries now, and I've worked for a whole alphabet soup of agencies and donors and everything else. Mainly what I do is to give policy advice to developing countries. I began working initially on trade policy, but now in the last decade, decade and a half, I've transitioned more towards environmental economics and environmental policy because the risks that are presented by climate change are going to come to dominate development agenda globally in the next generation so we need to have a much better support for developing countries because their capacity to adapt is much more limited than richer countries.

Interviewer: If you had to distill your research interests down into one essential question about human nature, what is it? Why are you interested in that?

Roland-Holst: Okay, about human nature? It's an immensely challenging subject. I mean, we work in a behavioral science and I find it extremely fascinating because humans are such complex organisms and we have to combine the insights of psychology, sociology, and all the social sciences to really understand what drives our economic decisions. For me, the fascination is probably analogous to what a field biologist would field when they go into a rainforest, or a marine biologist when they go into the coral reef environment. There's just a fantastic diversity and excitement in evolutionary processes, it's all there -- you just walk into an open market in a developing country and you get that same feeling, the vibrancy. The complexity can be really demanding for us, to try to come up with theories that explain human behavior, but the real motivation for doing that -- for me at least -- is to improve livelihoods. That's been my main goal since I decided to make this transition. Let's be honest, this thing we call prosperity is very much a work in progress. When 40% of humanity is living on less than 3$ a day, it's hard to say that the 400 years since the Industrial Revolution have really been a complete success. When you live in a place like California, you can kind of become complacent. We have an enormous amount of work to do and it's becoming even more challenging as we see the constraints emerge on global resource use.

Interviewer: Would you say climate change is the biggest restraint?

Roland-Holst: I think that's the biggest challenge facing humanity, for sure. For the early part of my generation, we had this impression that Malthus was dead and we had overcome the threat of exhausting our own habitat, but now, unfortunately, that's coming back to haunt us. We once thought that the Earth was so vast that we could exploit it relentlessly without ever seeing the consequences of doing that -- except maybe locally, in terms of things like toxic pollution and so on. But now we're really beginning to realize that we're touching the envelope of our own survival and that's a new thing, and frankly speaking, being part of my generation I feel really guilty about that, you know, it's this sort of "OK Boomer" problem. Since I have to spend my days looking out at audiences full of faces like yours, I want to have hope for the future. And for that reason, I am really, firmly committed to trying to find direct solutions to these problems. We're fortunate -- you're fortunate - to be in a place where people respect science and evidence so it's a more constructive environment. But still, the challenges of denial and everything else is really substantial. My job, as I see it, is to strengthen the basis of evidence, to help find ways to make all of this not only more sustainable but continue to improve livelihoods for those who haven't attained the material aspirations that all of us enjoy.

Interviewer: What are the common problems you run into when advising countries and policymakers?

Roland-Holst: There are big geographic differences, of course. There's a kind of deadlock between Washington and California, and I do most of my work in California and in East Asia on environmental work, and those are really positive areas to work. I mean, clearly, there are more challenges in East Asia as far as emissions and environmental risks go, but I'll tell you something that I find very heartening. Most of the policymakers that I've dealt with in Asia are pragmatists, they're pragmatic. They respect science. They may say that this isn't our first priority right now, but they aren't in denial about our material facts, and so eventually, I expect that they're going to come around.

And this is our challenge, I think, is to raise the standards of policy to meet the evidence, and frankly speaking most of the policymakers I talk to in Europe and in Asia are much more pragmatic. They have priorities of course, and those priorities order the decision that they make, but they're not in denial about science. And when they need to come around I expect that they will. For example, China is now the most aggressive country in the world when it comes to improving air quality, and it's not because we were guilt-tripping them about emissions and telling them they need to stop global warming, it's because they have a public health crisis in their cities right now. That brought them onto the bandwagon a sense of realistic concern about the quality of life for their own citizens. Thank goodness, you know, I hope other countries will follow suit. India needs to do that. They may not have the same authoritarian organizational capacity as China -- well, in principle, they might -- but the risk is becoming completely intolerable, so they really have to come around, and I hope that they will

Interviewer: So what do you say is something that policymakers get about economics that the average person won't?

Roland-Holst: I find that actually, very frustrating, that in many cases I see the same constraints of ignorance and denial.

Interviewer: Even though they have more information?

Roland-Holst: They should know better. They have one thing that's really working against them and it's not stupidity, it's not ignorance, it's political opportunism. In many cases, we'll see policymakers make decisions for political reasons, which essentially deft the evidence that experts are trying to present to them, whether its scientific evidence or economic evidence, they say "No, don't tell me that, because I need to do this for other reasons." This is something you do see, I have to say, frequently in some developing countries because you have oligarchic power structures in those countries, so the policymakers are responding to different kinds of incentives, which are not necessarily dictated by what we consider to be evidence or expert opinion. They have to respond to political priorities, shall we say. I understand that it's pragmatic in a way, but it is deeply frustrating, and the worst example of that is, of course, corruption. It's real, we can't deny it, and it's a very efficient organism in some institutional settings. In that context, the absence of corruption is a good thing but still, even in countries with relatively low corruption like the United States -- relatively, corruption exists everywhere in the world -- but even with relatively low corruption there are still political forces that compromise, I wouldn't say the judgment of decision-makers, but the decisions that they actually take. I think in many ways they know better, but that doesn't stop them from doing it -- making a decision that's not in the interest of most of their constituency.

That's the most frustrating thing for me, shortsightedness and I would say policy bias, we just have to call it that. Whether it's a result of corruption or some other kind of influence -- expediency -- it's frustrating. If you look at the social polarization of the US right now, that's a really classic example of that. It's trying to appease a really small minority of swing voters in order to ensure, or to try to assure -- I don't know if it'll work or not -- but unfortunately the last time it seemed to have worked, and so we're only going to see that ramp up again, but it's all the wrong decision making.

I'll give you a really good example. The country of Brazil spends half of its education budget on university education; That's serving 4% of the population. That's craziness, not only from an equity point of view but also from an economic development point of view. For a country like that with relatively low average education levels to put half their education budget into 4% of the population is absurd. But if you ask -- I was in a meeting at the World Bank where the Minister of Education was challenged on this -- he said "Well, you know, I can't justify this policy, but I can tell you why it exists. It's because most members of the National Legislature want their children to go to college. Those ate the people who allocate the budget, but it's a policy that has no economic rationale; on the contrary, it's really destructive because it's just perpetuating inequality, but it's happening for political reasons.

Interviewer: What are the major problems facing developing countries today, and what is the most interesting solution to that problem? Or memorable, it doesn't have to be a good solution.

Roland-Holst: No, there are very good solutions out there. Most of them involve basically a lot of very diligent participatory economics. It's really basically ownership and accountability is the best solution in a development context. One of the most chronic sources of poverty and inequality is weak property rights. People have no incentive to invest. It's not just that they may have enough to properly start with but they don't even have an incentive to invest in what they do possess because they are afraid it'll be expropriated. You learn this at the beginning of your economics classes, that prosperity is all based on savings and investment. That's the growth cycle, that's the engine of growth. So poverty, global poverty, is not so much a low-income trap, it's a low investment trap. That's what keeps people in a low-income status. The way we got out of poverty, all the great societies, is that we were low income once but then we started to save and invest, save and invest, build, build, build, build capacity, build infrastructure, it's all through savings and investment. The poor have savings -- They are poor, of course, but if you don't believe they have savings then go to a wedding, go to a funeral, and you'll see a lot of money being spent from savings. That's being s-ent on social capital because they have secure property rights socially but when it comes to land tenure and other things that they could invest in productively, property rights are too weak. Rights reform, which means inclusive, democratic, participatory development, is the most important foundation because it allows the poor to engage in self-directed poverty alleviation. They'll do it themselves as we all did. They'll invest their way out of poverty, they can, but in most developing countries they don't have the security to, it's much too risky for them to because they can't secure their property rights. So that's the big challenge that I would say. On the climate issue, I wouldn't say that it’s come out of nowhere but for developing countries it has. Most developing countries have no significant responsibility for climate change. Of course, India and China are big emitters, because they’re big countries. But otherwise, these countries are going to face enormous forward financial obligations just for security. And my fear is that development is going to start going in reverse if we don't redouble our commitments to help them because they don't have the capacity alone to adapt. There's going to have to be some kind of North-South solution to these things. People ask me all the time when I speak about climate, what's going to trigger this response, how are we going to get over the denial, and my answer is: I hope this doesn’t happen, but ultimately it’ll end with the beginning of the zombie movie when people start moving in very large numbers. That’s it, because countries will react, the rich countries will recognize they have to. Look at what happened in this crisis in the Middle East, this tragedy in Syria and the neighboring countries. Just a few hundred thousand refugees completely upended the European political system. This resurgence of the right -- incredible, right? We’re talking about numbers that are a hundred times larger. Climate refugees, the UN is calling 50-100 million by 2050.

Interviewer: I remember reading that by 2100 it would be 2 billion.

Roland-Holst: We’re not ready for that. But if it starts, like zombie movies, people are going to react, in a very bad reaction. Because that theme is always the same in those crazy movies, you know, it's like “we’re coming to take what you possess and nothing’s going to stop us” and the only reaction to that is violence. So I hope that that isn't what triggers the end of denial, but if we keep denying it that’s going to be the only alternative because people can't stay. Bangladesh is looking at 40 million refugees. They’re the poster child of sea-level rise -- they’re going to lose almost 20% of their landmass by 2040 and those people don’t have a place to go yet. I’ve counseled the Bangladeshi government about this and I’ve said: look, migration is a very positive force for growth, and it has been for many countries, but only when it’s demand-driven. You’ve got to basically get around and in front of this thing, create the capacity, create the jobs, create the residential infrastructure to bring migrants, not to wait for them to come running into these areas because that will only arouse hostility. So, big challenges.

Professor Jeeyang Rhee Baum

*Interviewed by **Ally Mintzer***

Jeeyang Rhee Baum is an Adjunct Lecturer in Public Policy at the Harvard Kennedy School of Government. Her research focuses on the political economy of administrative reform, particularly as it relates to accountability, transparency, and public participation in policy development in East Asia.

Interviewer: I'd like to first talk about your personal journey and how it has led to your research in public policy in East Asia. Can you describe your background and what experiences led you to discover your passion for public policy?

Baum: Yes! I went to public policy school for my master's degree, since at the time I was very interested in studying how government decisions are made. Then I did a summer internship with the State Department and was assigned to the embassy in Nepal. Through that internship, I discovered that there was a whole democratization process that not only Nepal was going through, but a lot of other countries as well. Essentially, my interests started to go more and more towards international development. After the State Department internship, I moved to Washington D.C., where my goal was to work in international development. However, I ended up taking a job in the Executive Office of the President at the Office of Management and Budget. There, I learned what public policy decision making in the executive branch of the United States was like. But I was not working on East Asia or Nepal or international development—I was working on transportation issues.

Interviewer: Also important.

Baum: Yes, exactly! Through studying different modes of transportation, I gained a lot of knowledge about infrastructure finance, interest group politics, and R&D programs. Currently, I teach corruption and development, and a lot of those issues have to do with infrastructure. After working at the OMB, I eventually went back to get my PhD in political science at UCLA because I kept asking more questions and wanted to get back to international development issues.

Interviewer: What inspired you to research public policy in

East Asia, in particular?

Baum: To get into my doctoral program, I wrote a paper on Brazil's democratization and development policies. When I got to school, I found myself moving more and more towards "my roots," as my adviser called it, specifically in South Korea and its neighboring countries. When I had to write my dissertation proposal, I decided not to focus on Brazil and focus instead on the East Asian democracies. I found that the problems I was interested in had to do with my experience in government: how executive branches differ across countries, how policies are developed in the executive branch across countries, and then more generally how our laws pass and are designed.

Interviewer: What are some areas you are researching right now and how are you collecting your data?

Baum: I'm working on several areas: I don't know if you want me to talk about all of them...

Interviewer: Yes! I'd love that.

Baum: One area is looking at the different ways bureaucracies restructure themselves after democratic transition. I'm measuring the different types of organizations or regulatory measures that different governments adopt with respect to how policies are made and who gets to participate. It's kind of an extension of my first book, which was about APAs [administrative procedure acts]. Much of this data involves translating legislation and coding it. The goal is to get accurate, qualitative data and then try to standardize it empirically so that eventually we can conduct statistical analysis.

Another area I'm looking at is why some political parties in various countries are adopting primaries for presidential nominations and others are not. There hasn't yet been a satisfactory explanation for why this happens in some of the new democracies in East Asia, specifically Korea, Taiwan, and Japan (a long time ago).

My last research project has more to do with corruption in East Asia and beyond. I'm trying to understand the relationship between the frequency of reporting of political scandals in various media sources. Arguably, there has been a substantial rise in political scandals being reported by various media outlets, so I'm trying to understand this increase and if there are underlying causes that might explain why the frequency has gone up.

Ally Mintzer: Have you formed any conclusions thus far as for why there has been such a rise in scandals in the media?

Baum: I don't have a definitive conclusion, but I have my suspicions. Forming such a conclusion involves separating the cause and effect: is it that there are more corruption scandals in real time, or does the media now have the freedom to report more scandals? I don't know which yet. However, I hypothesize the increase of reported scandals has something to do with interparty competition. There is a new unseen level of political competition, whereas before single parties dominated the political apparatus. With political democratization, there is much more alternation between party representation in government and more incentive for parties vying for the same office to potentially use the media.

Interviewer: I think you touched on your book "Responsive Democracy: Increasing State Accountability in East Asia," where you discuss APAs that aim to govern how federal agencies create policies and regulations. One particular country you discussed extensively was South Korea: can you elaborate on how the country's economic state led to the passage of their APA in 1994?

Baum: South Korea's economic state was a very critical impetus for why the APA passed when it did. This was an era of globalization, and the president that came into power was the first civilian president since democratization. He was coming into an international scene where Korea was a member of the Organization for Economic Cooperation & Development and the World Trade Organization: they had a lot to prove and faced organizational pressure. Essentially, this was the era of deregulation. The state had to withdraw its heavy hand in the economy and direct the country towards more regulatory frameworks that were consistent with the OECD's standards. And in this ripe post-economic growth era where they had taken care of basic needs, they were suddenly finding themselves worrying about environmental cleanup and social issues that required a kind of framework. The APA was one option, and the politics were ripe enough for the passage.

Interviewer: A long-standing debate in economics is the conflict between regulation and economic growth. What are your thoughts on this?

Baum: This question is huge. I am certainly not an expert on this particular question—there are a lot of academics that focus squarely on this relationship and dynamic. Based on my research and thinking with respect to the countries I know more about (I want to caveat that), I think that it's about finding the right balance depending on the context. Different times in a particular country might require more or less regulation relative to their neighbor. It depends on your comparative advantage and what kind of government you have. For the East Asian NICs [newly industrialized countries] of Taiwan, Hong Kong, Singapore, it made sense for them coming out of, say, the Korean War for Korea's case or WWII, to rebuild. It made sense for authoritarian, single-party governments to have a heavy hand in directing and steering the economy without contending with activists and interest groups. At this time, heavy regulation led by the state was essential for economic growth. But then, after the takeoff when growth rates began to wane, they had to switch gears and deregulate, become less heavy handed, and allow for other regulatory actors to have a stake in economic policies. Otherwise, the government would have been toppled. All these political factors matter; it's fairly complex.

Politics is messy. I believe that while you can have an economic theory driving certain sets of macroeconomic policies, at the end of the day you have to factor in the local politics. That's where I think general theories or models of economic development fall short.

Interviewer: At Harvard, you're currently teaching a course on corruption. Are there any particular trends regarding corruption: is it on the rise or falling?

Baum: This is a really good question. In the past two decades, especially in political science, it's become one of the focal points for comparative politics. Before, corruption was mainly studied on a case-by-case level, with less attention to cross-national analysis. Before, both from the policy world and academia, there was an understanding that corruption would go away or we wouldn't see the distorted effects of corruption hampering a country's economic growth if we democratized the country. But that hasn't happened. There are a whole bunch of countries where even with democratization, corruption got worse.

The international organization Transparency International has a corruption perception index that measures the perception of political corruption from experts. The survey began in the 90's and is done annually in 180 countries. This past year, they said that corruption is going up, including in the US. However, while it allows us to compare across countries, it's highly problematic because the index is based on perception—which isn't to say that they aren't helpful at all, we look at them all the time and study them in class. But it's different from measuring actual corruption or even experience-based corruption.

There are lots of different types of corruption, from grand corruption, extortion, embezzlement to petty theft. The easiest way to divide them is corruption based on need or greed. One prevalent definition of greed-based corruption is the misuse of public office for private gain, like using money from taxation for private gain. An example of need-based corruption is bribes that a consumer might have to pay in order to see the doctor. This is a necessity and everyone is doing it—if you don't do it, you don't get the vaccine. Most corruption falls into one of the two categories, but there is also a gray area.

Interviewer: What made you pursue academia rather than work in industry?

Baum: Because most people went to academica! *Laughs* No, but it's a good question, especially now. When I got my PhD at UCLA, in those days the reason why you got a PhD was to go into academia or a think tank. I was already working in government, so I knew I wouldn't give up my job for the next 6 years if I wasn't going to go into academia. I certainly had friends (not many though) that went to apply for organizations that require the skills you get through a PhD, say, McKinsey, or think tanks like the RAND Corporation. Now there are a lot of people that pursue other academic work with a PhD. For me, there was never a question. Sometimes I think maybe I should have questioned it *laughs* but I think for me it was always about the notion of the "revolving door"—or whether to go through that revolving door. I always wanted to be consulting governments, countries, or organizations that are creating policies. In academia, I love to always think about issues and be informed by practitioners; that's why I love teaching at the Kennedy School. Also, I wanted to teach! My dad was an economics professor, so I grew up in an environment always talking about politics. I always loved the idea of thinking all the time. Somebody once asked me what other job pays you to read all day? Maybe you should consider it too! And you get summers off too—sort of.

Professor Meredith Lynn Fowlie

*Interviewed by **Vanessa Thompson***

Dr. Meredith Lynn Fowlie is an environmental and energy economist, and Professor at the University of California, Berkeley. Her work investigates market-based environmental regulation, such as emissions trading programs, and the demand-side of energy markets. Dr. Fowlie was very generous to share her work and findings with BER Staff Writer, Vanessa Thompson, in the following interview:

Interviewer: How did you first get into economics? Why did you choose energy economics in particular?

Fowlie: Long story short, I was interested in finding solutions to environmental problems. I initially thought that these crises could be solved by studying the science behind these problems. I did my undergraduate at Cornell in Ecology and Sustainable Agriculture. I soon realized that the science was relatively far along, and that the crux of these problems often had more to do with the economic incentives that guide the choices we make. So, I got my Master's in Environmental Economics.

When I was working with a Canadian Aid project in Pakistan and Afghanistan, I intended to work on a project involving sustainable agriculture, microcredit and women's groups. But in the end, I ended up working with a team of engineers who were working on local micro-hydro developments. It was super interesting. It had elements of engineering/science, economics, and touched on gender issues. We had to ask questions like: If we bring electricity to these villages, who will benefit and how? It had so many threads.

They got me involved and put me on whatever aspects of the project they needed help. And it turned out to be really fascinating in terms of thinking about how to value rural electrification, who benefits from these developments, and how to set up the cost recovery mechanisms so that these projects can sustain themselves.

Interviewer: As someone interested in economics and policy regarding energy, what are some places we can look for discovering our own specialty in this field?

Fowlie: If you are interested in policy, there are a number of agencies in California that can offer exciting and stimulating career opportunities: CARB, PUC, CEC.

In my past research projects I have worked closely with electric utilities (investor owned and municipal utilities). More recently I am starting to get involved with our Community Choice Aggregator (East Bay Clean Energy). These entities need to stay a few steps ahead of the policies that impact their investments and operations. So these can be really interesting places to work if you are interested in energy and environmental policy. The electricity sector has been—and will continue to be—a focus area for climate change mitigation.

We also have Environmental Economic & Policy alumni at influential think tanks and advocacy groups such as NRDC, the Natural Resource Defense Council, and E3, which is a consulting firm that does a lot of the analysis for the PC. There are several places you can look if you're interested in policy.

Interviewer: If we are interested in learning more about this type of data analysis, what resources would you recommend?

Fowlie: One resource I would recommend is the Dlab on campus. They have Python boot camps. They run a bunch of boot camps, which probably won't get you to the level needed, but at least it signals that you have got some basic familiarity.

Interviewer: As we explore professions and interests, what is your experience or recommendations when looking at energy markets abroad? Regarding electricity systems outside the US, what programs are you aware of that help developing countries?

Fowlie: In developing and emerging economies, the emphasis and priorities can look different as compared to here in the U.S. I am working with some collaborators at IIT Bombay on a project that aims to accelerate the adoption of more efficient appliances. In this context, rural electrification and expanding access to reliable and affordable energy sources is an essential priority. So when we are thinking about what kind of investments make the most sense, we need to think about both energy savings potential, but also economic development objectives.

Interviewer: Within the US, I'm also curious about how difficult it is to push for renewables like solar in colder climates with less sun access as well as political environments that are not as supportive of renewables. What do you see as the best ways to reduce our carbon emissions in places like Minnesota or the Midwest who tend to have less sun and also less of a political push for green infrastructure than California?

Fowlie: There are these fantastic resource maps that the National Renewable Energy Laboratory showcases. They've assessed the wind and solar potential across the country. And you might be surprised at the solar energy generation potential even in colder climates.

Recent work by researchers at LBNL have been assessing both the resource potential and the costs of increased RE penetration. Here in California, they have found that fairly aggressive targets (e.g 80%) are within reach and would not significantly increase generation costs. But as you push beyond that, costs start to really escalate given the intermittent nature of solar and wind.

Interviewer: Do you think it's possible to improve public transportation?

Fowlie: It's a really important question. Vehicle's miles traveled (VMT) in the United States have been increasing. Some of this is related to housing affordability issues here in California. We're seeing more driving. As people are pushed out of the city due to urban housing prices, they're having to buy a car when they didn't have to before. I see an important role of investments in public transit in terms of supporting our decarbonization goals. I do fear that the current pandemic is a setback for public transit. We had a hard time convincing people to get out of their cars and onto the BART before COVID-19. I fear that argument is going to get even harder to make. At least in the near term.

Fowlie: Thank you so much for your time. As a prospective professional interested in working in the private sector, but also interested in policy, do you have any recommendations?

In California, there are a lot of private companies or industrial companies that need policy experts. Many host policy workshops to find these professionals so they can understand the policy environment and anticipate the changes. There are lots of opportunities for policy work. I recommend looking at our alumni networks and utilizing our resources.

Interviewer: Thank you so much for your time and insights.

Measuring the Impact of MiFID II on Information Asymmetries using Microstructure Models

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Abstract

This paper evaluates the impact of the Markets in Financial Instruments Directive II (MiFID II) regulation on information asymmetries. The microstructure models of Madhavan, Richardson, and Roomans (1997) and Glosten and Harris (1988) are adapted to estimate potential changes in adverse selection of German stocks traded at the Cboe Europe Equities exchange. To classify trades in the presence of uncertainty regarding the sequence of trades and quotes within a second, a robust classification method is developed. I find a short-term increase in adverse selection and transaction cost after the MiFID II implementation. A long-term reduction of information asymmetries due to the regulation is indicated and discussed.

Acknowledgment

"I greatly appreciate the opportunity to write my thesis at the Chair of Econometrics, Statistics and Empirical Economics at the University of Tuebingen. In particular, I thank my supervisor Joachim Grammig, especially for his support in choosing an adequate model and estimation method to address the research question. I thank Johannes Bleher for his exceptional support: he collected and provided the data, developed the idea of an extended tick-rule, gave further suggestions about developing the analysis and assisted in coding the estimation procedures. Special thanks to Thomas Dimpfl for providing the idea of a rolling parameter estimation."

Table of Contents

List of Tables

List of Figures

1 Introduction

In efficient security markets, all market participants have the same expectation of the fundamental security value. The resulting prices immediately incorporate new public information because traders revise their beliefs about the fundamental value. In the presence of information asymmetry, informed traders take advantage of their private information by buying (selling) securities if their expectation of the fundamental security value is higher (lower) than the market price. Rational uninformed traders protect themselves from informed trading by adjusting their quotes and by revising their beliefs based on the actions of other market participants. This adaptation in trading strategies and behavior typically leads to less price efficiency and higher transaction costs. These consequences are called adverse selection. Therefore, regulators such as the European Union seek to reduce information asymmetries by implementing laws and supervising financial markets. The Markets in Financial Instruments Directive II (MiFID II 2014) and the associated Markets in Financial Instruments Regulation (MiFIR) came into effect on January 3rd, 2018, to replace the previous framework MiFID I and expand the scope to cover non-equities.[1] Improved investor protection, market resilience, efficiency and transparency for all market participants are the main goals of MiFID II (European Securities and Market Authority 2019).

Reducing market fragmentation by limiting dark pool and over-the-counter (OTC) trading and homogenizing tick sizes is supposed to increase competition and price efficiency while driving down transaction cost. Post-trade transparency is enhanced by extended reporting obligations for dark pool and OTC trading. The newly applied reporting standards for non-equities could also reveal relevant information for equity

1 From now on, MiFID II and MiFIR will be discussed together under the name MiFID II.

markets.[2]

Whether MiFID II successfully reduces information asymmetry and therefore adverse selection within equity markets is evaluated using two market microstructure models. The Madhavan-Richardson-Roomans model (1997) and the Glosten-Harris model (1988) state that in addition to new public information, the observed order flow is informative and reveals private information about the fundamental value of a security. While Madhavan et al. use the suprise in order flow to measure adverse selection, Glosten and Harris assume high trade volumes to be informative. The models are adapted to measure a potential change in adverse selection. The paper is organized as follows. Section 2 describes the two microstructure models and explains the price formation process, the spread decomposition and the estimation procedures used. Section 3 describes and analyzes the data used for the effect estimation and discusses the method of trade classification. The model parameter and spread estimates are presented and discussed in Section 4 while the impact of the MiFID II implementation on adverse selection is evaluated in Section 5. Section 6 concludes and proposes further research ideas.

2 Microstructures

2.1 Model Description

Market microstructure models are able to analyze market frictions such as asymmetric information while accounting for the basic trading mechanisms. The model proposed by Roll (1984) shows that without asymmetric information, the fundamental security value μ_t fluctuates randomly due to the uncorrelated newly available public information u_t. Trade

2 Detailed information on the regulations impacting market transparency can be obtained from the MiFID II directive (2014) and its supplements or from the European Securities and Market Authority
(2019).

indicator models add the concept of informed trading to the basic framework provided by the Roll model. Since both informed and uninformed traders operate within the market, the order flow will provide a noisy signal about the fundamental security value μ_t. Therefore, market participants also revise their beliefs about μ_t depending on the private information revealed by the order flow. The trade indicator variable x classifies transactions as buyer initiated $(x = 1)$, seller initiated $(x = -1)$ or neither buyer nor seller initiated $(x = 0)$. The Madhavan et al. model assumes that surprises in the sequence of trade indicators x are informative. The revision in beliefs due to adverse selection depends on the surprise in order flow $x_t - E(x_t|x_t-1)$ and degree of information asymmetry $\boldsymbol{\theta}$. The post-trade expected security value μ_t in Eq. (1) includes the revision in beliefs both due to order flow as well as new public information u_t. According to the Glosten and Harris model, higher trade volumes v_t are associated with informed trades. This is captured in the adverse selection component z_t in Eq. (2).

Madhavan et al.: $$\mu_t = \mu_{t-1} + \theta\left(x_t - E(x_t|x_{t-1})\right) + u_t \quad (1)$$

Glosten-Harris: $$\mu_t = \mu_{t-1} + z_t x_t + u_t \quad (2)$$

Without informed trading, these processes will be reduced to a random walk with parameters θ and zt equal to zero. Rational liquidity providers set ask (bid) quotes conditional on the trade being buyer (seller) initiated (see Madhavan et al. 1997, 1040). The cost of providing liquidity such as direct transaction fees, specialist rent, inventory holding cost and potential profits for market makers are combined in the transitory component ϕ (Madhavan et al.) or ct (Glosten-Harris). The transitory component is uncorrelated with the fundamental value and simply added or subtraced from the conditional post-trade fundamental value depending on the trade indicator xt (see Eq. (3)/(4)).[3]

Madhavan et al.: $$P_t = \mu_t + \phi x_t \quad (3)$$

Glosten-Harris: $$P_t = \mu_t + c_t x_t \quad (4)$$

3 I drop the independent and identically distributed rounding error x with mean zero for simplicity.

Madhavan et al. include the possibility of trading at the mid-quote with unconditional probability $P(x_t = 0) = \lambda$. On the other hand, because Glosten and Harris originally assume that trades are executed at the quoted bid and ask prices, the model framework also applies to trades with $x_t = 0$.

For the unspecified Glosten-Harris model, the transitory component ct and the adverse selection component z_t both include a constant and a volume-dependent parameter.

Glosten-Harris: $$c_t = c_0 + c_1 v_t$$

$$z_t = z_0 + z_1 v_t$$

Furthermore, the Madhavan et al. model derivations 1 and 2 in the appendix show that the surprise in order flow can be written using the first-order autocorrelation of the order flow ρ.

Madhavan et al.: $$E(x_t | x_{t-1}) = \rho x_{t-1} \tag{5}$$

The post-trade expected value of the security (see Eq. (1)/(2)) is combined with the transitory component (see Eq. (3)/(4)) to form the price P_t for both models. To estimate the model parameters, the price changes ΔP_t are calculated to remove the unobservable fundamental value μ_{t-1} (see derivation 3 for Madhavan et al.).[4]

Madhavan et al. $$\Delta P_t = (\phi + \theta)x_t - (\phi + \rho\theta)x_{t-1} + u_t$$

Glosten-Harris $$\Delta P_t = c_0 \Delta x_t + c_1 \Delta(x_t v_t) + z_0 x_t + z_1 x_t v_t + u_t$$

Inserting the additional adverse selection components into the basic models yields the following price changes for the extended models:

4 To be precise, u_t here includes the change in the rounding error $\Delta\xi$ instead of ξ as in Eq. (3) and (4).

Madhavan et al.: $\theta = \theta_0 + \theta_1 d_t$

Glosten-Harris: $z_0 = z_{0,0} + z_{0,1} d_t$

$z_1 = z_{1,0} + z_{1,1} d_t$

Inserting the additional adverse selection components into the basic models yields the following price changes for the extended models:

Madhavan et al. $$\Delta P_t = \left(\phi + \theta_0 + \theta_1 d_t\right)x_t - \left(\phi + \rho(\theta_0 + \theta_1 d_t)\right)x_{t-1} + u_t \quad (6)$$

Glosten-Harris $$\Delta P_t = c_0 \Delta x_t + c_1 \Delta(x_t v_t) + (z_{0,0} + z_{0,1} d_t) x_t + (z_{1,0} + z_{1,1} d_t) x_t v_t + u_t \quad (7)$$

The quoted bid-ask spread $s_{Q,t}$ calculated as the difference between bid and ask price is an easily observable a priori measure for potential transaction cost. The model implies that quoted spread is obtained by calculating the implied quotes, which are conditioned on the trade indicator (see Eq. (1),(3) / (2),(4)). The Glosten-Harris spreads include trade volume v_t and are therefore time-dependent.

Madhavan et al. $$s_Q = 2(\theta + \phi) \quad (8)$$

Glosten-Harris $$s_{Q,t} = 2(c_t + z_t) \quad (9)$$

The effective spread sE for a buyer (seller) initiated trade is defined as twice the difference between the transaction price (prevailing midquote) and the prevailing midquote (transaction price). It takes into account trading inside the spread and the effect of large orders going through multiple layers of the order book. The derivation for the Madhavan et al. model spread excluding x = 0 is provided by Theissen and Zehnder (2014). Since trades within the spread are supposed to execute exactly at the midquote, the effective spread is zero for x = 0. The resulting expected effective spreads equal the quoted spreads in Eq. (8) and (9) times the probability of a trade at the bid or ask.[5]

Madhavan et al. $$s_E = 2(1-\lambda)(\theta+\phi) \quad (10)$$

Glosten-Harris $$s_{E,t} = 2(1-\lambda)(c_t+z_t) \quad (11)$$

The realized bid-ask spread $s_{R,t}$ measures the cost of a round-trip and takes into account the price impact of the first transaction.[6] Due to the possibility of trading inside the spread, the realized spreads for both models depend on the trade indicator in t.[7] The computations of the expected realized spreads and the realized spreads conditional on the trade indicator are shown in the appendix (derivations 4 / 5).

Madhavan et al. $$s_R = (1-\lambda)(2\phi+\theta) \quad (12)$$

Glosten-Harris $$s_{R,t} = (1-\lambda)(2c_t+z_t) \quad (13)$$

Without the autocorrelation parameter ρ of the Madhavan et al. model or the volume dependent components c_1 and z_1 of the Glosten and Harris model, both models are equivalent to the model proposed by Huang and Stoll (1997) with a constant adverse selection and a constant transitory parameter.

2.2 *Estimation*

For the nonlinear extended Madhavan et al. model, the vector of model parameters $\beta_{MRR} = (\rho,\lambda,\varphi,\theta_0,\theta_1)$ is estimated using the generalized method of moments (GMM). GMM requires exactly identifiable parameters and an ergodic weakly stationary stochastic process for consistent parameter estimates, but no additional assumptions about the underlying data distribution. The main idea of a method of moments estimator is

5 I denote λ also as the share of trades with x = 0 for the Glosten-Harris model.

6 Madhavan et al. call this the effective spread

7 In their paper, Glosten and Harris (1988) do not allow for trades between the quotes so the effective spread $s_{R,t} = 2c_t + z_t$ only depends on the traded volume.

to choose the estimated parameter vector $\hat{\beta}_{MRR}$ so that the sample moments match a defined set of moment equations. When the number of independent moment conditions m is equal to the number of estimated parameters k, the model is exactly identified. The unique solution of the minimization problem sets the difference of the sample moments and the moment conditions to zero given a sufficiently large sample (method of moments). For over-identified models where $m > k$, such as the extended Madhavan et al. model, one can usually only choose $\hat{\beta}_{MRR}$ to closely match sample and population moments. Hansen (1982) shows that the estimated parameters $\hat{\beta}_{MRR}$ are still consistent and asymptotically normally distributed. I used the iterated GMM with a Newey-West estimator[8] of the covariance matrix of mo- ment conditions So to obtain $\hat{\beta}_{MRR}$ and the heteroskedasticity consistent covariance matrix of parameters.[9]

The following 7 moment conditions are used to estimate the parameter vector$\hat{\beta}_{MRR}$ and a constant drift α.

$$E = \begin{pmatrix} x_t x_{t-1} - \rho x_t{}^2 \\ |x_t| - (1-\lambda) \\ u_t - \alpha \\ (u_t - \alpha)x_t \\ (u_t - \alpha)x_{t-1} \\ (u_t - \alpha)d_t x_t \\ (u_t - \alpha)d_t x_{t-1} \end{pmatrix} = 0$$

with $$u_t = \Delta P_t - (\phi + \theta_0 + \theta_1 d_t)x_t + (\phi + \rho(\theta_0 + \theta_1 d_t))x_{t-1}$$

8 The chosen number of lags equals the nearest integer of To:25 with T as the number of observations (see Greene, 2003, p.142).

9 For a detailed description of the methodology, see Hayashi (2000, pp.204-214, 454-486).

The first moment equation defines the first-order autocorrelation of the order flow, the second the probability of trading inside the spread, and the third the constant price drift. The last four equations state the orthogonality of newly available public information to the regressors x_t, x_{t-1}, $d_t x_t$ and $d_t x_{t-1}$.

The Glosten-Harris price change in Eq. (7) is estimated with ordinary least squares, which can be seen as a solved case of the method of moments with the orthogonality assumptions as moment conditions. While Glosten and Harris state that OLS is not efficient because of round-off errors and a possibly time-dependent variance of ut, the estimated coefficients $\hat{\beta}_{GH}$ will still be consistent and the white covariance matrix of parameters accounts for heteroskedasticity.

The implied model spreads are consistently estimated by using the estimated model parameters $\hat{\beta}$ instead of the true population parameters β for the quoted spreads in Eq. (8) and (9). However, due to a potentialy different probability of trades inside the spread λ before and after MiFID II, the effective and realized spreads are calculated per observation instead of using Eq. (10), (11), (12) and (13). For the Glosten-Harris model, this additionally removes the bias of possibly correlated trade indicators and volumes.

3 Data

3.1 Source and Selection

The data was scraped by PhD candidate Johannes Bleher from the chair of Econometrics, Statistics and Empirical Economics at the University of Tuebingen. The website netfonds.no of the Norwegian Netfonds bank AS (2018) gives users access to trading on Scandinavian, US and European exchanges. The stocks in the sample are traded via the Cboe European Equities exchange[10], which is the

10 BATS Europe Exchange was rebranded to Cboe European Equities in 2017.

largest European stock exchange with 23.14% market share for DAX stocks (see Cboe European Equities 2019a, market statistics by index). The BXE and CXE integrated books are anonymous central limit order books with both displayed and hidden liquidity for European equities. The main allowed order types for integrated books are as follows: displayed and non-displayed limit orders, displayed and non-displayed market orders within the order price collar (1% of the European Best Bid and Offer[11]), iceberg orders, displayed and non-displayed pegged orders using the Primary Best Bid and Offer[12], displayed and non-displayed post only orders for market making, and sweep orders that access both the BXE and the CXE integrated order book (Cboe European Equities 2019b, 23-26). Continu- ous trading is possible from 9:00am to 5:30pm (CET) with an opening and a closing auction. Apart from the integrated order books, Cboe European Equities provides a periodic auction book and a separate dark book for non-displayed orders (see Cboe European Equities 2019b, 5-6).

The original sample contains separated integrated order book and transaction data on 203 German equities from October 2017 to March 2018. Securities with less than 5000 observations from December 2017 to January 2018 were removed. Since higher impacts of the aggregation methods in Section 3.2 on actively traded assets might bias the results, the 10 most liquid assets of the sample were also excluded. Therefore, the sample contains 50 stocks with 5000 to 52000 transactions from December 2017 to January 2018. To compare short- and midterm effects, model estimation is done for a two-month time frame[13](December to January) and a six-month time frame (October to March). SAS On Demand for Academics 9.4 and SAS University Edition 9.4 (basic edition) were used for data processing,

11 The European Best Bid and Oer is the best price available in European central limit order books of regulated markets.

12 Xetra quotes for German equities.

13 The time frame contains 20 trading days before and 22 after the implementation of MiFID II.

model estimation and test implementation.

3.2 *Trade Classification and Aggregation*

The widely used method for inference of trade direction proposed by Lee and Ready (1991) requires the price Pt, the best bid $P_{b,t}$ and the best ask Pat at transaction time t. A trade is classified as a buy (sell) if the transaction price P_t is higher (lower) than the midquote. If the transaction price is equal to the midquote, the tick test classifies the trade by tracing back to the price change: if it was an uptick (downtick), the trade is classified as a buy (sell).

Since the time variable t is only measured in seconds for the position and the trade data, time stamps with multiple quote changes do not allow for the determination of prevailing quotes at the transaction time. Due to large changes in quotes within a second, using the average bid and ask quotes per second would reduce the accuracy of trade identification. Therefore, an alternative method is employed based on the highest observed bid quote $P_{b,t}^{max}$ and the lowest observed ask quote $P_{a,t}^{min}$ during a second. A trade is classified as a buy if $P_{b,t}^{max}$ is smaller than P_t and $P_{a,t}^{min}$ is equal to or smaller than P_t. A trade is classified as sell if $P_{b,t}^{max}$ is equal to or greater than P_t and $P_{a,t}^{min}$ is greater than P_t. The remaining trades are classified as trades which were neither buyer nor seller initiated with $x = 0$. This method should classify most buys and sells with ordinary order types correctly. Observations that could be a buy or a sell according to the displayed quotes are uncertain and therefore signed as neither buyer nor seller initiated.[14]

For multiple transactions within a second, the occurrence order is uncertain. As large trades are split up into multiple observations if they go through multiple layers of the order book, the trade volume v and the first-order serial

14 This method of trade classification was proposed by PhD candidate Johannes Bleher from the chair of Econometrics, Statistics and Empirical Economics at the University of Tuebingen.

correlation of order flow ρ are biased.[15] To correct for this, a majority rule determines the trade indicator and aggregates price and volume to a single trade observation per second.[16] This method leads to unbiased model estimates if all observations within a second belong to one transaction and the trade indicators are the same. For multiple transactions within the observations of the same trade indicator, the Madhavan et al. autocorrelation coefficient ρ and the trade-volume dependent Glosten-Harris coefficients c_1 and z_1 will be downwards-biased.

Depending on the number of trades for the security, 55-80% of the trade observations are impacted by quote aggregation and 5-20% are impacted by trade aggregation. 30-45% of the trades are classied as inside the spread.Transactions before and after the ocial trading hours from 9:00am to 5:30pm (CET) are deleted. Overnight price changes are removed because the opening auction price changes typically do not follow the same distribution as price changes for continuous trading (see Amihud and Mendelson, 1987).

3.3 Descriptive

Table 1 provides average mean, standard deviation, skewness and excess kurtosis for relevant variables before and after the implementation of MiFID II. Figures 5 to 16 in the appendix show the distribution of means across securities as a histogram and a as time series plot. All variables are

15 Trade volume v is underestimated for larger trades. r is overestimated because one transaction splits up into multiple observations with the same trade indicator x.

16 The volume-weighed trade indicator for all trades within the second is calculated. For $x >= 1/3$, the aggregated indicator x_t is set to 1, for $1/3 > \bar{x} > 1/3$, $x_t = 0$ and for $\bar{x} <= -1/3$ follows $x_t = -1$. For the aggregated trade observation per second, the accumulated volume and the volume-weighed average price of all observations with $x_{t,i} = x_t$ is used. If $x_t = 0$ and no observation fulfills $x_{t,i} = x_t$, then the accumulated volume and the volume-weighed average price of all observations within the second is used.

Table 1: Descriptive statistics (Dec. 2017 - Jan. 2018)

	Mean		Std.Dev.		Skewness		Excess kurtosis	
	before	after	before	after	before	after	before	after
P	72.244	75.48	1.465	1.423	0.498	0.195	13.369	1.191
ΔP	0.000	-0.008	3.458	3.546	-1.100	-0.498	41.386	37.200
x	0.002	-0.003	0.021	0.022	0.119	0.157	-0.156	-0.121
v	11.590	12.254	21.194	27.601	1.424	1.415	3.556	5.553
$tr./day$	502.595	580.671	135.412	136.625	0.347	0.831	0.636	4.903
s_Q	8.070	7.004	7.759	5.979	3.118	3.557	25.446	18.368
s_E	1.346	1.400	4.472	3.036	2.374	2.334	32.443	24.310
$r_{Q,MQ}$	12.060	9.620	11.646	5.091	3.145	3.557	25.654	18.436
$r_{E,MQ}$	1.955	1.893	7.076	2.525	2.504	2.320	33.376	25.054

Note. This table presents the descriptive statistics for key variables from December 1st, 2017, to January 31st, 2018. The mean, standard deviation, skewness and excess kurtosis of the individual security distributions are reported before and after the implementation of MiFID II. The following variables are included: price *P* in Euro, price change between trades *ΔP* in cent, trade indicator x, quoted/effective spread s_Q/s_E in cent, volume per trade v in 1000 shares, transactions per day *tr./day*, relative quoted/effective spread $r_{Q,MQ}/r_{E,MQ}$ in basis points.

positively skewed with positive excess kurtosis[17] except for the trade indicator.

Prices rose in December and fell slightly in January with similar standard deviation and decreasing kurtosis for price *P* and price change ΔP.[18] More buys (sells) than sells (buys) occurred for the period of increasing (decreasing) prices. The daily distribution for the trade indicator in Figure 10 shows that the share of buys (sells) varied from about 40% to 60% of the transactions.[19] The Madhavan et al. assumption of *E(x)*

17 Excess kurtosis is defined as kurtosis -3. If positive, the distributions kurtosis is higher than the kurtosis of the normal distribution.

18 The mean price difference cannot be entirely explained by the mean price change DP because overnight price changes are deleted.

19 This is a simplied interpretation of the trade indicator assuming that all trades are either buys or sells.

= 0 might not hold for the time frame because of a possible correlation of the trade indicator and short term price movements.

Trade volume *v* and the number of trades per day *tr./day* increased from December to January, which could have various reasons such as the inactivity during the Christmas break in December or new portfolio allocations and strategies in the new year. However, the distribution of trade volume *v* is highly susceptible to data aggregation (see Section 3.2). The shift in mean trade volume could be caused by a higher number of trades which increases the probability of aggregating multiple trades within a second. This might also explain the positive skewness and kurtosis of trade volume (see Figure 11). The higher number of trades per day in January could also be caused by increased attractiveness of the Cboe trading venue. This may indicate a successful shift of trading volume to more structured market places as intended by MiFID II.

Quoted spreads decreased by 1.0 cents from December to January while effective spreads increased marginally. Standard deviations fell sharply for both measures. The low ratio of effective to quoted spread is partly caused by trades inside the spread. In addition, the fact that best bid and best ask vary within a second could lead to more sells (buys) at higher bid (lower ask) quotes while s_Q and s_E are calculated using averages. Still, the considerable difference between quoted and effective spread reduces their validity as observed measures of transaction cost. The relative spreads $r_{Q,MQ}$ and $r_{E,MQ}$ compare the spread to the midquote and are used as a standardized measure for different security prices. The relative effective spread $r_{E,MQ}$ decreased by 3.2% compared to the 4.0% increase for the effective spread. This indicates that absolute effective spreads are not proportional to security prices.

The same descriptives for the time frame from October 1st, 2017, to March 31st, 2018 are provided in Table 4. Price movement, trading activity and spread changes all have the same directions as for the smaller time frame. Price volatility increased for the period from January to March and effective spread volatility is constant compared to the decrease in Table 1.

From January 2nd to January 3rd, tick sizes increased for 38 securities of the sample and stayed constant for 12 securities due to the introduction of the MiFID II ticksize regime.[20] An increase in minimum tick size generally increases spreads and transaction cost (Verousis, Perotti, and Sermpinis, 2018). Boyde, Yang, Campbell, and Naidoo (2018) and a paper published by the french financial markets regulator Autorite des Marches Financiers (2018)[21] show that the minimum tick size regime of MiFID II is the main determinant of relative quoted spread changes for individual securities. Relative quoted spreads for DAX stocks with an rise in minimum tick size increased by 35.6%, the overall average increased by 8.9% (see Boyde et al., 2018, p.6). These findings are not confirmed by the decreasing relative quoted spreads for the Cboe data. Unequal sample composition and trading venues could be one reason for the deviant effect. Besides, the discrepancy could be caused by the average quoted spread calculation which is not time-weighed for the Cboe quotes.

For consistent estimation results, weakly stationarity of price changes is required. The Dickey-Fuller test rejects the null hypothesis of non-stationary price changes for all securities on a 1% significance level.

4 Empirical Results

4.1 Parameter Estimates

20 The minimum tick size for each stock in the sample is determined by sorting the quotes in ascending order and calculating the smallest difference between quotes. Taking differences of the minimum tick size on January 3rd and January 2nd in 2018 yields the change in minimum tick size for a security assuming no signicant change in price or trading activity.

21 Authors unknown.

Table 2: Parameter estimates (Madhavan et al., Dec. 2017 - Jan. 2018)

	all securities				*single securities - significant β_i*			
	$\overline{\hat{\beta}_i}$	$\overline{\hat{\sigma}}_{\hat{\beta}_i}$	$\hat{\sigma}_{\overline{\hat{\beta}_i}}$	P	$H_0:$	$\beta_i = 0$	$\beta_i >= 0$	$\beta_i <= 0$
ρ	0.1087	0.000074	0.0036	<0.01%		100%	0%	100%
λ	0.3922	0.000020	0.0042	<0.01%		100%	0%	100%
ϕ	0.6910	0.000036	0.0765	<0.01%		100%	0%	100%
θ_0	0.3207	0.000111	0.0966	0.17%		68%	12%	58%
θ_1	0.3021	0.000154	0.0768	0.03%		74%	10%	66%
α	-0.0021	0.000018	0.0048	66.21%		6%	10%	0%

Note. The table presents summary statistics of the Madhavan et al. model parameters estimates based on data from December 1st, 2017, to January 31st, 2018. The mean of estimated parameters $\overline{\hat{\beta}_i}$ and the mean of estimated parameter standard deviations $\overline{\hat{\sigma}}_{\hat{\beta}_i}$ are given with i denoting the individual securities. The estimated standard deviation of the mean estimated parameter $\overline{\hat{\sigma}}_{\hat{\beta}_i}$ is used to compute the p-value for the two-sided t-test on $\overline{\hat{\beta}_i}$. On a single security level, the share of significant parameters for two-sided and one-sided tests on a 5% level is provided. The parameter mean and standard deviation for ϕ, θ_0, θ_1 and α are denoted in cent.

Table 2 shows summary statistics of the Madhavan et al. parameter estimates. Auto-correlation of order flow $\hat{\rho}$ is positive as assumed by the model. 39.22% of the trades are classied as neither buyer nor seller initiated. The transitory parameter estimate $\hat{\phi}$ with 0.69 cents is more than twice as large as the estimated adverse selection parameter before MiFID II $\hat{\theta}_0$ with 0.32 cents. The additional adverse selection parameter in January, $\hat{\theta}_1$, is comparable in size to $\hat{\theta}_0$, which leads to a combined adverse selection parameter of 0.62 cents after MiFID II. The drift estimate $\hat{\alpha}$ is economically insignificant. Without knowledge of the parameter distribution, the mean of parameter estimates $\overline{\hat{\beta}_i}$ is still assumed to be normally distributed, so a t-test on the mean parameter can be conducted. The p-value for this test shows that all parameters except the drift a are significantly different from zero on a 1% level. On an individual level, the share of significant parameters for two-sided and one-sided tests supports the overall t-test results. The first-order autocorrelation parameter ρ, the share of trades inside the spread λ and the transitory parameter ϕ are significantly greater than zero for all stocks on a 5% signicance level. For the adverse selection parameters θ_0 and θ_1, the null hypothesis of a parameter value smaller or equal to zero is rejected for 58% and 66% of stocks respectively. After the MiFID II implementation, the combined adverse selection parameter θ is significantly greater than zero for 47 stocks on a 5% level.

The parameter estimates for the six months estimation period in Table 7 are similar for ρ, λ, θ_0 and α. The estimated transitory component $\hat{\phi}$ is 0.08 cents lower and the MiFID II adverse selection component $\hat{\theta}_1$ 0.16 cents higher for the longer estimation period. The adverse selection parameters θ_0 and θ_1 are significantly greater than zero for 76% and 86% of stocks respectively. The combined adverse selection parameter after MiFID II is significantly greater than zero for all stocks.

Compared to the Madhavan et al. (1997) estimates for a sample of 274 NYSE stocks in 1990, the parameters are notably different in size.[22] Higher autocorrelation (0.38), less trades inside the spread (30%) and substantially higher transitory (4.18) and adverse selection (3.14) parameters for the NYSE sample signies a change in market dynamics and efficiency from 1990 to 2017. Theissen and Zehnder (2014) use signed transaction and spread data for DAX stocks traded at XETRA in 2004 to estimate the Madhavan et al. (1997) model. Their mean estimated transitory parameter $\hat{\phi}$ with 0.48 cents is slightly lower than for the Cboe sample, which could be explained by lower direct transaction costs for the highly liquid DAX-stocks. While the on average smaller capitalized stocks in the Cboe sample are expected to have higher adverse selection costs (see Frey and Grammig, 2006), $\hat{\theta}$ is higher for the DAX sample than for the Cboe sample even after the MiFID II implementation (0.70 cents to 0.62 cents). The higher DAX autocorrelation of 0.22 combined with the Madhavan et al.

22 The parameters are reported over 5 intra-day trading intervals. The mean of parameters is used for comparison with the German sample.

(1997) estimate of 0.38 supports the idea that the trade aggregation process imposes a negative bias on the autocorrelation parameter r for the Cboe sample (see Section 3.2).

Table 5 presents the Glosten-Harris parameter estimates for the two month time frame. The mean constant transitory parameter $\hat{c}_0$ with 0.72 cents is significantly different from zero, which is supported by the tests on a single security level. The mean volume-dependent transitory parameter $\hat{c}_1$ per 100 shares is significant according to the overall t-test, but on the individual level only 40% of stocks reject the null hypothesis of $c_1 = 0$. For the average trade volume of 12000 shares (see Table 1), the volume-dependent component is 0.08 cents, which is marginal compared to the constant transitory component. Nevertheless, since trade volume is positively skewed, some securities and observations will have sizable volume-dependent transitory components.[23] The constant transitory parameters $z_{0,0}$ and $z_{0,1}$ are both positive and significant according to the overall t-test. The test results for single stocks are less clear. Only for 68% of the sample the parameters are significantly different from zero, 68% of individual parameters for $z_{0,0}$ and 62% for $z_{0,1}$ are significantly greater than zero. The combined constant adverse selection parameter z_0 after MiFID II is equal in size to the constant transitory component and significantly greater than zero for 96% of the stocks. The volume-dependent adverse selection parameters $\hat{z}_{1,0}$ and $\hat{z}_{1,1}$ are both negative, but $\hat{z}_{1,1}$ is statistically and economically insignificant. For the average trade volume, the volume-dependent adverse selection component is -0.38 cents which is similar to the base constant adverse selection parameter $\hat{z}_{1,1}$ in absolute value. The combined parameter z_1 is significantly different from zero for 70% of stocks after the MiFID II implementation. According to a multiple restriction Wald test,

23 The upper 5% confidence interval for the daily mean trade volume in Figure 12 is about 45000 shares per transaction, which would lead to a volume-dependent transitory component of 0.32 cents. A median volume of about 7000 shares per transaction would lead to a volume-dependent transitory component of 0.049 cents.

the overall adverse selection component is significantly different from zero for 41 stocks before and 48 stocks after the MiFID II implementation.[24]

The differences of the Glosten and Harris (1988) estimates for the longer time frame in Table 8 are similar to the differences for the Madhavan et al. (1997) estimates. The constant transitory parameter $\hat{c}_0$ and the base constant adverse selection parameter $\hat{z}_{0,0}$, are 0.05 cents lower, the MiFID II constant adverse selection parameter $z_{0,1}$ is 0.12 cents higher for the longer estimation period. The combined volume-dependent adverse selection parameter $\hat{z}_1$ is closer to zero before and after MiFID II for the longer time frame, but the additional MiFID II parameter $\hat{z}_{1,1}$ is more relevant. The combined parameter z_0 after the MiFID II implementation is significantly greater than zero for all stocks. The overall adverse selection component is significantly different from zero for 48 stocks before and all stocks after the MiFID II implementation.

The model specification without c_1 and z_0 proposed by Glosten and Harris (1988) is rejected for 41 stocks before and 48 stocks after the MiFID II implementation using a Wald test. The size and direction of the volume-dependent adverse selection component for the German sample do not support the hypothesis of higher trade volumes indicating informed trading. Both the Madhavan et al. and the Glosten-Harris overall model are significant for all stocks.

Comparing the model parameter estimates, the transitory parameters $\hat{\phi}$ an $\hat{c}_0$ are almost equal in size. This is not surprising since they both measure non-persistent effects and are incorporated in the models in the same way. The constant adverse selection parameter before MiFID II $\hat{\theta}_0$ is smaller

24 Ho before MiFID II: $z_{0,0} = 0$, $z_{1,0} = 0$. Ho after MiFID II: $z_{0,0}+z_{0,1} = 0$, $z_{1,0}+z_{1,1} = 0$.

than $\hat{z}_{0,0}$, which might partly be due to the negative volume-dependent parameter $\hat{z}_1$ that has to be compensated. The assumed MiFID II effect on adverse selection is measured by q1, z0;1 and the negligible volume-dependent parameter $\hat{z}_{1,1}$. Constant adverse selection components for both models are similar in size and significantly positive for two out of three stocks. For the six months estimation period, the additional adverse selection parameters are larger and significantly positive for five out of six stocks.

4.2 *Spread Estimates*

The economic implications of the parameter estimates are assessed by investigating the model implied spreads (see Eq. (8) to (11)) as measures for transaction cost.

Table 3: Spread estimates (Madhavan et al., Dec. 2017 - Jan. 2018)

	Mean		*Std.Dev.*		Paired t-Test
	before	after	before	after	P
s_Q	2.023	2.627	2.094	2.415	0.03%
$r_{Q,Data}$	26.482	37.755	11.442	10.555	<0.01%
s_E	1.261	1.573	1.278	1.501	0.20%
$r_{E,Data}$	90.590	110.013	26.719	22.876	<0.01%
r_{Adv}	17.602	41.751	34.734	16.332	<0.01%

Note. The table presents summary statistics of the Madhavan et al. model parameters estimates based on data from December 1st, 2017, to January 31st, 2018. The mean of estimated parameters $\overline{\hat{\beta}_i}$ and the mean of estimated parameter standard deviations $\overline{\hat{\sigma}}_{\hat{\beta}_i}$ are given with i denoting the individual securities. The estimated standard deviation of the mean estimated parameter $\hat{\overline{\sigma}}_{\hat{\beta}_i}$ is used to compute the p-value for the two-sided t-test on $\overline{\hat{\beta}_i}$. On a single security level, the share of significant parameters for two-sided and one-sided tests on a 5% level is provided. The parameter mean and standard deviation for ϕ, θ_o, θ_1 and α are denoted in cent.

Table 3 presents the Madhavan et al. implied spreads, the share of implied to observed spread and the share of implied spread attributable to adverse selection before and after the application of MiFID II. A paired t-test on difference in means before and after the implementation date is conducted and indicates a significant change in means for all variables and both models. The required normal distribution of differences plotted in Figures 3 and 4 is unlikely to hold for all variables. Therefore, the significance of the changes in means according to the paired t-test should be evaluated with caution.

From December to January, the implied quoted spread s_Q increased from 2.02 cents to 2.63 cents, which is caused by the positive additional adverse selection parameter $\hat{\theta}_1$. The observed quoted spread is highly underestimated as shown by the low share of implied to observed quoted spread $r_{Q,Data}$. The observed quoted spread decreased after the MiFID II implementation whereas the implied quoted spread increased. Madhavan et al. (1997) argue that their systematic underestimation of the quoted spread by a third might be caused by a higher probability of midquote transactions when spreads are large.

The implied effective spread s_E is 0.31 cents higher after the MiFID II implementation while the observed spread marginally increases by 0.05 cents. Using Eq. (12), the approximated implied change in realized spread sR from December to January is 0.18 cents $(=(1-\hat{\lambda})\hat{\theta}_1)$.[25]Increasing transaction cost measured by sE and sR is attributed to a higher adverse selection component of the spread. The model implied effective spread underestimates the observed effective spread by 9.6% before and overestimates it by 10.0% after the implementation. In comparison to the 1.26 cents (before MiFID II) or 1.573 cents (after MiFID II), Theissen and Zehnder (2014) report average effective spreads of 2.36 cents for the DAX sample without trades inside the spread. Furthermore, Theissen and

25 This simplied calculation of s_R relies on the expected realized spread in Eq. (12) rather than the conditional realized spread per observattion. If l differs in the time before and after the MiFID II implementation, the two methods do not yield the same result.

Zehnder (2014) provide evidence for a 20% downwards bias of implied spreads of trade indicator models caused by negative serial correlation of new public information and the trade indicator. This bias cannot be found for the Cboe sample. Adding the fact of reasonable parameter estimates for the Cboe sample when compared to the results of Theissen and Zehnder (2014) supports the assumption that the aggregated observed effective spreads are probably inaccurate (see Sections 3.2 and 3.3).

For the six months time frame, the assumed adverse selection effect is larger with 0.88 cents for s_Q and 0.51 cents for s_E compared to the 0.60 cents and 0.31 cents for two months (see Table 9). The Glosten-Harris spread estimates in Tables 6 and 10 are comparable in size for the estimates before and after the MiFID II implementation.

5 Impact Evaluation

The validity of the measured MiFID II eect on adverse selection depends upon the capability of the chosen microstructure models to quantify adverse selection, the data quality and the ability to attribute the eect to the MiFID II changes. Ness, Ness, and Warr (2001) state that the adverse selection measures of Madhavan et al. (1997) and Glosten and Harris (1988) are related to volatility and the share of informed traders at the market, but not correlated with other adverse selection measures. Both models focus on the information content of the order flow while for instance neglecting the information revealed by the open limit order book. The Glosten and Harris (1988) idea of higher trade volume revealing private information is not supported by the results for the Cboe sample. The distribution of the volume-dependent parameter in Figure 24 suggests that most stocks display a negative volume-dependent effect, though there is no clear direction of the effect for all stocks. This result can partly be attributed to the use of algorithms or order types such as iceberg orders that can split up large orders to reduce price impacts. The negative eect could be caused by uninformed traders who are required to move large volumes to meet their required portfolio composition or risk tolerance level without having the time or the resources to minimize price impacts. Moreover, the impact of aggregating trade volume on the measured effect (see Section 3.2) is hard to assess as it might depend on individual stock characteristics such as trading activity, price and / or volatility. The Madhavan et al. (1997) assumption of a positive serial correlation of the order flow holds for the Cboe sample. Although the assumed quote revision due to surprise in order flow rˆ x seems low with 0.03 cents before and 0.07 cents after MiFID II for x 6= 0, Section 4.1 provides an indication of the downwards-biased autocorrelation. Furthermore, the ability to estimate adverse selection with serially correlated trade indicators is an advantage compared to the Glosten and Harris (1988) model. Hence, the Madhavan et al. (1997) results might be more appropriate as an adverse selection measure for the Cboe sample than the Glosten and Harris (1988) results.

The discrepancies in model implied spreads and observed spreads shown in Section 4.2 are a sign of poor model performance. However, the high share of quote observations affected by aggregation increases uncertainty of the quoted observed spread and the midquote which is used to determine the observed effective spread. Although the transactions used for the model estimation are signed by using quote data, the sign rule in Section 3.2 declares uncertain trades as inside the spread. Even if the trade aggregation process weakens the estimated effect size of serial correlation and trade volume, the models still incorporate the basic Huang and Stoll (1997) idea that order flow is informative. As a consequence, the model implied spreads based on transaction data might be more suitable to determine the prevailing spread at the time of the transaction than the aggregated observed spreads. Additionally, implied and observed effective spreads are similar and the assumed MiFID II change is positive for both.

The Madhavan et al. (1997) model parameter $\hat{\theta}_1$ of 0.3021 cents implies 0.31 cents higher effective spreads and approximately 0.18 cents higher realized spreads in January 2018 than in December 2017. For the six months estimation period, $\hat{\theta}_1$ with 0.4385 cents implies 0.51 cents higher effective and approximately 0.27 cents higher realized spreads for January to March 2018 than for October to December 2017. The direction of the measured effect is not as expected for the MiFID II regulations, which are supposed to increase market transparency and therefore reduce the adverse selection component of transaction cost.

Indeed, it cannot be followed that the measured change in adverse selection is attributable to the implementation of MiFID II on January 3rd, 2018. Other events in the estimation time frame after January 3rd might have also caused adverse selection to rise. To further evaluate this, the Madhavan et al. (1997) and Glosten and Harris (1988) extended models are estimated for event dates from November 2017 to February 2018 with a rolling estimation window of two months. The event date is the date for the activation of the additional adverse selection parameter/s. Figures 1, 2 and 17 to 26 show the rolling parameter estimates for both models. The mean rolling parameter estimate for the additional adverse selection parameter q1 in Figure 1 rises from 0.0 cents in mid-November to 0.3 cents for the last days of December and the first days of January. After that, $\hat{\theta}_1$ steadily decreases to 0.1 cents at the start of February, then drops down to -0.1 cents. The adverse selection parameter for the whole estimation time frame qˆ0 in Figure 2 remains about constant for November and December. Logically, it increases from the start of January 2018 to mid-February from 0.32 cents to 0.8 cents because the dropped out additional parameter q1 has to be explained by q0 before the event. Figures 21 and 22 show a similar relationship for the constant adverse selection parameters ˆz0;1 and ˆz0;0 for the Glosten and Harris (1988) model. The volume-dependent additional parameter ˆz1;1 gradually increases from mid-December with -0.1 cents per 10000 shares to 0.0 cents at the year change to a high of over 0.1 cents in the last third of January and falls down to -0.1 cents afterwards.

On the one hand, the peak of the additional adverse selection parameters at the turn of the year provides evidence for a relevant change in adverse selection during that time. Positive falling parameters for the month of January imply the interpretation of long-term effects rather than additional events. Although many events at the start of January 2018 possibly impact information asymmetries for stocks, MiFID II fundamentally changes transparency and functionality of financial markets as a whole. Therefore, MiFID II is presumably the main event impacting changes in information asymmetry.

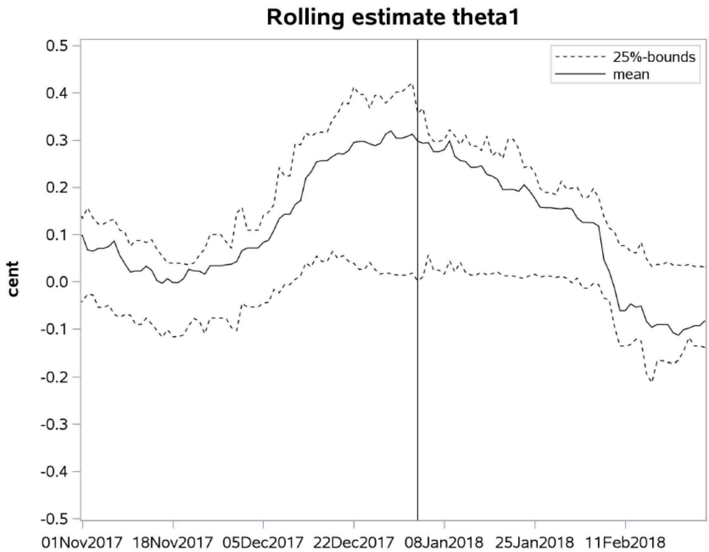


Figure 1: Rolling parameter estimate $\hat{\theta}_1$

Note. This figure plots the mean estimated Madhavan et al. parameter $\hat{\theta}_1$ for event dates from November to February with a two months es- timation time frame. Starting from the event date, the additional adverse selection parameter is active. The vertical line displays the MiFID II implementation date.

On the other hand, if only the MiFID II implementation influenced adverse selection at that time, the rise of the additional adverse selection effect would start in early December, not in mid-November. This observation could be explained by early adaptations of market participants to the regulations. Seasonality or other unrelated changes in volatility of newly available public information, share of informed traders and trading activity are likely to impact adverse selection. For instance, the approaching release of annual financial statements and new strategic announcements are plausible reasons for increased information asymmetry at the start of the year. The length of the estimation time frame does not allow to detect and control for these patterns. Additionally, effects

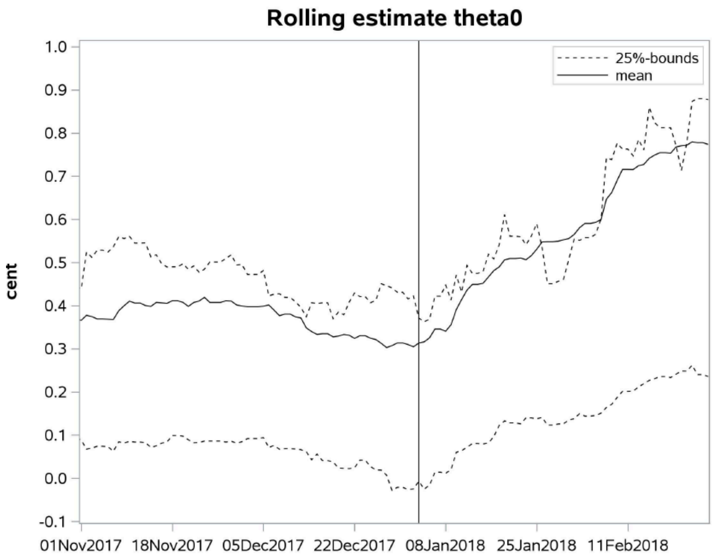


Figure 2: Rolling parameter estimate $\hat{\theta}_0$

Note. This figure plots the mean estimated Madhavan et al. parameter $\hat{\theta}_0$ for event dates from November to February with a two months es- timation time frame. Starting from the event date, the additional adverse selection parameter is active. The vertical line displays the MiFID II implementation date.

of most regulations are unlikely to show immediately at the implementation date.[26]The drop of the additional adverse se-

26 The tick size band introduced by MiFID II is an exception because it was implemented at January 3rd and directly impacted the price formation process. The increasing

lection parameter $\hat{\theta}_1$ shown in Figure 1 at the start of February could be a long-term event effect. In the case of MiFID II, published transparency data was incomplete at first as not all market participants were prepared to fulfill the reporting requirements. For example the Double Volume Cap publication on dark pool trading volumes was delayed to March 7th by the European Securities and Markets Authority due to insufficient quality of the collected data (see European Securities and Market Authority, 2019). Also, adverse selection effects could persist longer than the actual information asymmetry since market participants cannot instantly incorporate newly available information into their trading behavior.

Collectively, despite evidence for higher adverse selection right after the MiFID II implementation, a reduction of adverse selection due to MiFID II in the long-run is more plausible than an immediate effect and cannot be rejected by the empirical results.

6 Conclusion

I evaluate the impact of the Markets in Financial Instruments Directive II (MiFID II) regulation on information asymmetries. The microstructure models of Madhavan et al. (1997) and Glosten and Harris (1988) are extended to measure the additional adverse selection eect after the MiFID II implementation date. A sample of 50 German equities traded at the Cboe European Equities exchange is used to estimate the models.

While the MiFID II transparency rules are expected to reduce information asymmetries, the results show more adverse selection after the regulation came into force on

sample mean transitory parameters f and co until the end of January imply higher inventory holding and direct transaction costs (see Figure 17 and 25). This is consistent with the increased minimum tick size for the majority of stocks at the MiFID II implementation date, which is included in the transitory parameter.

January 3rd, 2018. Estimated eective spreads are 0.31 cents higher in January 2018 than in December 2017. Rolling model estimation indicates a possible long-term reduction in adverse selection. I discuss the attribution of the adverse selection changes to MiFID II.

Further investigation of MiFID II eects could stretch the estimation time frame and increase sample size to detect more resilient long-run effects on adverse selection. Similarly, the change in inventory holding and direct transaction cost may be evaluated. Potential stock characteristics that determine the size of the estimated eects could be identied. Furthermore, the proposed extended microstructure models allow to examine eects of other events impacting information asymmetries on nancial markets.

7 Appendix

7.1 Derivations

Model assumptions (Madhavan et al.)

$$E(x) = 0 \tag{14}$$

$$P(x_t = x_{t-1} | x_{t-1} \neq 0) = \gamma \tag{15}$$

$$P(x = 0) = \lambda \tag{16}$$

$$P(x_t = -x_{t-1} | x_{t-1} \neq 0) = 1 - \gamma - \lambda \tag{17}$$

The Madhavan et al. model assumptions are necessary for the calculation of the price change and the model implied spreads. Eq. (14) states that the mean for the trade indicator is assumed to be 0. Eq. (15) defines the probability g of a transaction at the bid (ask) following a transaction at the bid (ask) and is expected to be greater than 0.5. The unconditional probability of a trade inside the spread is defined in Eq. (16) as l. The probability for a trade at the bid (ask) following a trade at the ask (bid) in Eq. (17) follows from Eq. (15) and (16).

Derivation 1: Autocorrelation of order flow ρ (Madhavan et al.)

$$\rho_t = \frac{E\left[\left(x_t - E(x_t)\right)\left(x_{t-1} - E(x_{t-1})\right)\right]}{\sigma_{x_t}\sigma_{x_{t-1}}}$$

$$\rho = \frac{E(x_t x_{t-1})}{\sigma_x^2}$$

$$\begin{aligned}\sigma_x^2 &= P(x=1)(1)^2 + P(x=-1)(-1)^2 + P(x=0)(0) \\ &= 1-\lambda\end{aligned}$$

$$\begin{aligned}E(x_t x_{t-1}) = \; & P(x_{t-1} \neq 0)\,P(x_t = x_{t-1} | x_{t-1} \neq 0)(1) \\ & + P(x_{t-1} \neq 0)\,P(x_t = -x_{t-1} | x_{t-1} \neq 0)(-1) \\ & + P(x_{t-1} \neq 0)\,P(x_t = 0 | x_{t-1} \neq 0)(0) \\ & + P(x_{t-1} = 0)(0) \\ = \; & (1-\lambda)\gamma - (1-\lambda)(1-\gamma-\lambda) \\ = \; & (1-\lambda)\left(2\gamma - (1-\lambda)\right)\end{aligned}$$

$$\rho = 2\gamma - (1-\lambda)$$

The general definition of the first-order autocorrelation is given in the first line. With $E(x_t)$ = 0 (see Eq. (14)) and $\sigma_{xt}\sigma_{xt-1}$ = σ_x^2 (weak stationarity assumption), the first-order auto correlation only depends on the constant variance σ_x^2 and $E(x_t x_{t-1})$. The probabilities in Eq. (16), (15) and (17) lead to $E(x_t x_{t-1})$, which is then divided by $(1-\lambda)$ to obtain ρ.

Derivation 2: Conditional expected trade indicator E(xt jxt�1) (Madhavan et al.)

$$\begin{aligned}
E(x_t|x_{t-1}=1) = \quad & P(x_t=1|x_{t-1}=1)(1) \\
& +P(x_t=-1|x_{t-1}=1)(-1) \\
& +P(x_t=0|x_{t-1}=1)(0) \\
= \quad & \gamma-(1-\gamma-\lambda) \\
= \quad & \rho
\end{aligned}$$

$$\begin{aligned}
E(x_t|x_{t-1}=-1) = \quad & P(x_t=1|x_{t-1}=-1)(1) \\
& +P(x_t=-1|x_{t-1}=-1)(-1) \\
& +P(x_t=0|x_{t-1}=-1)(0) \\
= \quad & (1-\gamma-\lambda)-\gamma \\
= \quad & -\rho
\end{aligned}$$

$$E(x_t|x_{t-1}=0) = \quad 0$$

$$E(x_t|x_{t-1}) = \quad \rho x_{t-1}$$

The conditional expected trade indicator $E(x_t|x_{t-1})$ can be expressed by the first-order autocorrelation ρ. With Eq. (14) and ρ = 2γ - *(1-*λ*)* from derivation 1, the expected trade indicator given the 3 different cases of x_{t-1} simplifies to ρ, -ρ and 0.

Derivation 3: Price change ΔP_t (Madhavan et al.)

$$\begin{aligned}
P_t = &\quad \mu_{t-1} + \theta\left(x_t - E(x_t|x_{t-1})\right) + \phi x_t + u_t \\
\Delta P_t = &\quad \mu_{t-1} + \theta\left(x_t - E(x_t|x_{t-1})\right) + \phi x_t + u_t \\
&- \left(\mu_{t-2} + \theta\left(x_t - E(x_{t-1}|x_{t-2})\right) + \phi x_{t-1} + u_{t-1}\right) \\
= &\quad \mu_{t-1} + \theta\left(x_t - E(x_t|x_{t-1})\right) + \phi x_t + u_t - \mu_{t-1} - \phi x_{t-1} \\
= &\quad \theta(x_t - x_{t-1}\rho) + \phi x_t - \phi x_{t-1} + u_t \\
= &\quad (\phi + \theta)x_t - (\phi + \rho\theta)x_{t-1} + u_t
\end{aligned}$$

The post-trade expected fundamental value in Eq. (1) is combined with the transitory component in Eq. (3) to form the transaction price P_t. When taking differences, the fundamental value is canceled out. With $E(x_t|x_{t-1}) = \rho x_{t-1}$ (see Eq. (5)), the price change ΔP_t can be described with the 4 model parameters ϕ, θ, ρ and λ, which is included in ρ (see derivation 1).

Derivation 4: Realized spread s_R (Madhavan et al.)

$$\begin{aligned}
s_R = &\quad \left|E[P_{t+k} - P_t]\right| \\
= &\quad \left|E\left[(\mu_{t+k-1} + \theta(x_{t+k} - E(x_{t+k}|x_{t+k-1})) + \phi x_{t+k} + u_{t+k}) - (\mu_t + \phi x_t)\right]\right| \\
= &\quad \left|E\left[(\mu_{t+k-1} + (\theta + \phi)x_{t+k} + u_{t+k}) - (\mu_t + \phi x_t)\right]\right| \\
= &\quad \left|E(\mu_{t+k-1}) - E(\mu_t) + E(u_{t+k}) + E\left[(\phi + \theta)x_{t+k} - \phi x_t\right]\right| \\
= &\quad \left|E\left[(\phi + \theta)x_{t+k} - \phi x_t\right]\right| \\
= &\quad (1-\lambda)^2(2\phi + \theta) + \lambda(1-\lambda)(\phi + \theta) + (1-\lambda)\lambda\phi + \lambda^2(0) \\
= &\quad (1-\lambda)(2\phi + \theta)
\end{aligned}$$

$$\begin{aligned}
s_R(x_t \neq 0) = &\quad P(x_{t+k} \neq 0|x_t \neq 0)(2\phi + \theta) + P(x_{t+k} = 0|x_t \neq 0)\phi \\
= &\quad (1-\lambda)(2\phi + \theta) + \lambda\theta
\end{aligned}$$

$$\begin{aligned}
s_R(x_t = 0) = &\quad P(x_{t+k} \neq 0|x_t = 0)(\phi + \theta) + P(x_{t+k} = 0|x_t = 0)(0) \\
= &\quad (1-\lambda)(\phi + \theta)
\end{aligned}$$

The expected realized spread s_R is the cost of a buy (sell) in t and a sell (buy) in $t + k$ when ignoring the effect of autocorrelation (see Madhavan et al., 1997, p.1050). Using the price process in Eq. (3) with Eq. (1), $E(u_t) = 0$ and $E(\mu_{t+k-1}) = \mu_t$ under the assumption of no autocorrelation yields a simplified expression for the expected realized spread without the fundamental value. The four fundamentally different potential changes are from ask to bid, midquote to ask, ask to midquote and midquote to midquote (see Madhavan et al., 1997, p.1050). The probabilities for the paths $(1-\lambda)^2$, $\lambda(1-\lambda)$,$(1-\lambda)\lambda$ and λ^2 and the corresponding cost $(2\phi + \theta)$, $(\phi + \theta)$, θ and zero lead to the expected realized spread s_E. The conditional realized spreads are calculated by only taking into account the possible paths based on the condition.

The expected realized spread s_R is the cost of a buy (sell) in t and a sell (buy) in $t + k$ when ignoring the effect of autocorrelation (see Madhavan et al., 1997, p.1050). Using the price process in Eq. (3) with Eq. (1), $E(\mu_t) = 0$ and $E(\mu_{t+k-1}) = \mu_t$ under the assumption of no autocorrelation yields a simplified expression for the expected realized spread without the fundamental value. The four fundamentally different potential changes are from ask to bid, midquote to ask, ask to midquote and midquote to midquote (see Madhavan et al., 1997, p.1050). The probabilities for the paths $(1-\lambda)^2$, $\lambda(1-\lambda)$, $(1-\lambda)\lambda$ and λ^2 and the corresponding cost $(2\phi + \theta)$, $(\phi + \theta)$, θ and zero lead to the expected realized spread s_E. The conditional realized spreads are calculated by only taking into account the possible paths based on the condition.

Derivation 5: Realized spread $s_{R,t}$ (Glosten-Harris)

$$\begin{aligned}
s_{R,t} &= \left|E[P_{t+k} - P_t]\right| \\
&= \left|E\left[(\mu_{t+k-1} + z_t x_{t+k} + c_t x_{t+k} + u_{t+k}) - (\mu_t + c_t x_t)\right]\right| \\
&= \left|E\left[(c_t + z_t)x_{t+k} - c_t x_t\right]\right| \\
&= (1-\lambda)^2(2c_t + z_t) + \lambda(1-\lambda)(c_t + z_t) + (1-\lambda)\lambda c_t + \lambda^2(0) \\
&= (1-\lambda)(2c_t + z_t)
\end{aligned}$$

$$s_{R,t}(x_t \neq 0) = (1-\lambda)(2c_t + z_t) + \lambda z_t$$

$$s_{R,t}(x_t = 0) = (1-\lambda)(c_t + z_t)$$

The Glosten and Harris (1988) realized spread derivation is similar to the realized Madhavan et al. (1997) spread in derivation 4. The cost for the paths $(2c_t + z_t)$, $(c_t + z_t)$, z_t and zero do not depend on the trade volume in $t + k$ because both parts of the round-trip use the same volume.

7.2 Tables

Table 4: Descriptive statistics (Oct. 2017 - Mar. 2018)

	Mean		Std.Dev.		Skewness		Excess kurtosis	
	before	after	before	after	before	after	before	after
P	71.504	72.194	2.497	3.262	- 0.054	-0.645	0.974	7.497
ΔP	-0.002	-0.017	3.477	4.048	3.732	-4.618	35.388	23.548
v	11.906	12.292	23.555	30.844	1.333	1.105	2.873	5.092
x	0.004	-0.008	0.020	0.018	0.904	0.708	0.414	0.236
$tr./day$	517.175	603.303	111.602	126.729	0.743	1.500	3.556	7.034
s_Q	8.057	7.721	11.543	9.414	4.205	1.725	40.793	5.920
s_E	1.321	1.390	5.792	5.972	4.209	-1.096	40.095	3.922
$r_{Q,MQ}$	11.809	11.015	13.976	8.041	4.248	1.666	40.823	4.851
$r_{E,MQ}$	1.912	1.899	6.999	4.721	4.313	-1.046	41.673	4.574

Note. This table presents the descriptive statistics for key variables from October 1st, 2017, to March 31st, 2018. The mean, standard deviation, skewness and excess kurtosis of the individual security distributions are reported before and after the implementation of MiFID II. The following variables are included: price P in Euro, price change between trades DP in cent, trade indicator x, quoted/effective spread s_Q/s_E in cent, volume per trade v in 1000 shares, transactions per day tr:=day, relative quoted/effective spread $r_{Q,MQ}/r_{E,MQ}$ in basis points.

Table 5: Parameter estimates (Glosten-Harris, Dec. 2017 - Jan. 2018)

	all securities				*single securities - significant β_i*		
	$\overline{\hat{\beta}_i}$	$\overline{\hat{\sigma}}_{\hat{\beta}_i}$	$\hat{\sigma}_{\overline{\hat{\beta}_i}}$	P	$H_0: \beta_i = 0$	$\beta_i >= 0$	$\beta_i <= 0$
c_0	0.7173	0.000046	0.0831	<0.01%	100%	0%	100%
c_1	0.0007	<0.000001	0.0002	0.10%	40%	4%	50%
$z_{0,0}$	0.3950	0.000147	0.0908	0.01%	68%	6%	68%
$z_{0,1}$	0.3213	0.000199	0.0874	0.06%	68%	12%	62%
$z_{1,0}$	-0.0032	<0.000001	0.0007	<0.01%	58%	68%	4%
$z_{1,1}$	-0.0003	<0.000001	0.0005	57.25%	34%	22%	12%

Note. The table presents summary statistics of the Glosten-Harris model parameters estimates based on data from December 1st, 2017, to January 31st, 2018. The mean of estimated parameters $\overline{\hat{\beta}_i}$ and the mean of estimated parameter standard deviations $\overline{\hat{\sigma}}_{\hat{\beta}_i}$ are given with i denoting the individual securities. The estimated stan- dard deviation of the mean estimated parameter $\hat{\sigma}_{\overline{\hat{\beta}_i}}$ is used to compute the p-value for the two-sided t-test on $\overline{\hat{\beta}_i}$. On a single security level, the share of significant parameters for two-sid- ed and one-sided tests on a 5% level is provided. The parameter mean and standard deviation for c_0, $z_{0,1}$ and $z_{0,1}$ are denoted in cent, the volume-dependent c_1, $z_{1,0}$ and $z_{1,1}$ in cent per 100 shares.

Table 6: Spread estimates (Glosten-Harris, Dec. 2017 - Jan. 2018)

	Mean		*Std.Dev.*		Paired t-Test
	before	after	before	after	P
s_Q	2.006	2.586	2.079	2.384	0.03%
$r_{Q,Data}$	26.271	37.132	11.240	10.374	<0.01%
s_E	1.284	1.596	1.294	1.528	0.18%
$r_{E,Data}$	92.324	111.409	26.664	23.179	<0.01%
r_{Adv}	12.623	36.874	31.861	15.710	<0.01%

Note. This table presents model-implied estimated Glosten-Harris spreads and spread ratios before and after the implementation of MiFID II from December 1st, 2017, to January 31st, 2018. The mean $\overline{\hat{s}_i}$ / $\overline{\hat{r}_i}$ and the estimator of the variance across the sample $\hat{\sigma}_{\overline{\hat{s}_i}}$ / $\hat{\sigma}_{\overline{\hat{r}_i}}$ are reported in cents for the quoted spread s_Q and the effective spread s_E. The shares of implied to observed spread $r_{Q,Data}$ and $r_{E,Data}$ and the share of implied spread attributable to adverse selection r_{Adv} are denoted in percent. P-values for the paired t-test on difference in means before and after the MiFID II implementation are given in percent.

Table 7: Parameter estimates (Madhavan et al., Oct. 2017 - Mar. 2018)

	all securities				*single securities - significant β_i*		
	$\overline{\hat{\beta}_i}$	$\overline{\hat{\sigma}}_{\hat{\beta}_i}$	$\hat{\sigma}_{\overline{\hat{\beta}_i}}$	P	$H_0: \beta_i = 0$	$\beta_i >= 0$	$\beta_i <= 0$
ρ	0.1100	0.000024	0.0028	<0.01%	100%	0%	100%
λ	0.3976	0.000007	0.0036	<0.01%	100%	0%	100%
ϕ	0.6069	0.000012	0.0692	<0.01%	100%	0%	100%
θ_0	0.3310	0.000041	0.0832	0.02%	80%	6%	76%
θ_1	0.4385	0.000066	0.0855	<0.01%	86%	4%	86%
α	-0.0035	0.000006	0.0034	31.62%	12%	18%	4%

Note. The table presents summary statistics of the Madhavan et al. model parameters estimates based on data from October 1st, 2017, to March 31st, 2018. The mean of estimated parameters $\overline{\hat{\beta}_i}$ and the mean of estimated parameter standard deviations $\overline{\hat{\sigma}}_{\hat{\beta}_i}$ are given with i denoting the individual securities. The estimated stan- dard deviation of the mean estimated parameter $\overline{\hat{\sigma}}_{\hat{\beta}_i}$ is used to compute the p-value for the two-sided t-test on $\overline{\hat{\beta}_i}$. On a single secu- rity level, the share of significant parameters for two-sid- ed and one-sided tests on a 5% level is provided. The parameter mean and standard deviation for ϕ, θ_o, θ_1 and α are denoted in cent.

Table 8: Parameter estimates (Glosten-Harris, Oct. 2017 - Mar. 2018)

	all securities				*single securities - significant β_i*		
	$\overline{\hat{\beta}_i}$	$\overline{\hat{\sigma}}_{\hat{\beta}_i}$	$\hat{\sigma}_{\overline{\hat{\beta}_i}}$	P	$H_0: \beta_i = 0$	$\beta_i >= 0$	$\beta_i <= 0$
c_0	0.6583	0.000014	0.0781	<0.01%	100%	0%	100%
c_1	0.0005	<0.000001	0.0001	<0.01%	60%	0%	66%
$z_{0,0}$	0.3460	0.000047	0.0733	<0.01%	76%	4%	78%
$z_{0,1}$	0.4653	0.000065	0.0933	<0.01%	86%	4%	82%
$z_{1,0}$	-0.0020	<0.000001	0.0005	0.05%	80%	80%	6%
$z_{1,1}$	-0.0008	<0.000001	0.0004	9.23%	44%	40%	12%

Note. The table presents summary statistics of the Glosten-Harris model parameters estimates based on data from October 1st, 2017, to March 31st, 2018. The mean of estimated parameters $\overline{\hat{\beta}_i}$ and the mean of estimated parameter standard deviations $\overline{\hat{\sigma}}_{\hat{\beta}_i}$ are given with i denoting the individual securities. The estimated stan- dard deviation of the mean estimated parameter $\overline{\hat{\sigma}}_{\hat{\beta}_i}$ is used to compute the p-value for the two-sided t-test on $\overline{\hat{\beta}_i}$. On a single secu- rity level, the share of signicant parameters for two-sided and one-sided tests on a 5% level is provided. The parameter mean and standard deviation for c_o, $z_{o,1}$ and $z_{o,1}$ are displayed in cent, the volume-dependent c_1, $z_{1,o}$ and $z_{1,1}$ in cent per 100 shares.

Table 9: Spread estimates (Madhavan et al., Oct. 2017 - Mar. 2018)

	Mean		*Std.Dev.*		Paired t-Test
	before	after	before	after	P
s_Q	1.876	2.753	1.920	2.446	<0.01%
$r_{Q,Data}$	25.237	36.599	10.677	9.806	<0.01%
s_E	1.140	1.649	1.134	1.515	<0.01%
$r_{E,Data}$	84.341	118.576	23.949	20.967	<0.01%
r_{Adv}	25.761	52.228	20.889	12.083	<0.01%

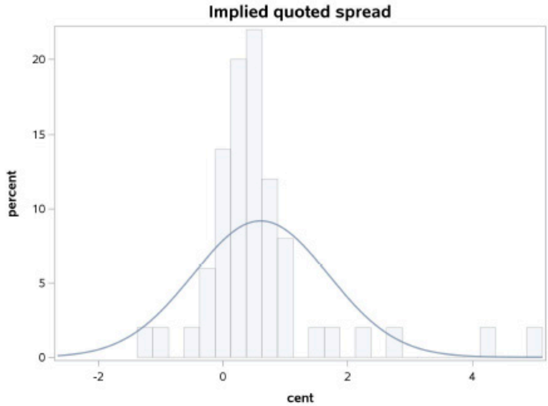
Note. This table presents model-implied estimated Madhavan et al. spreads and spread ratios before and after the implementation of MiFID II from October 1st, 2017, to March 31st, 2018. The mean $\overline{\hat{s}_i}$ / $\overline{\hat{r}_i}$ and the estimator of the variance across the sample $\hat{\sigma}_{\overline{\hat{s}_i}}$ / $\hat{\sigma}_{\overline{\hat{r}_i}}$ are reported in cents for the quoted spread s_Q and the effective spread s_E. The shares of implied to observed spread $r_{Q,Data}$ and $r_{E,Data}$ and the share of implied spread attributable to adverse selection r_{Adv} are denoted in percent. P-values for the paired t-test on difference in means before and after the MiFID II implementation are given in percent.

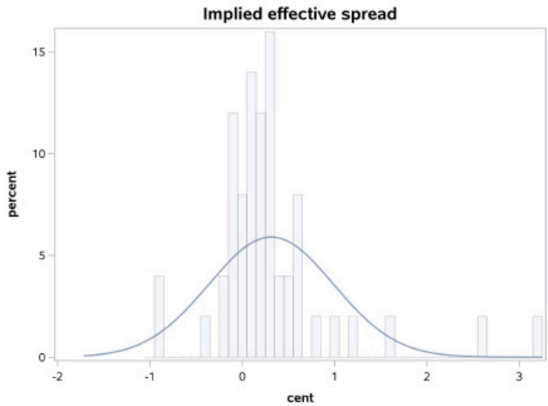
Table 10: Spread estimates (Glosten-Harris, Oct. 2017 - Mar. 2018)

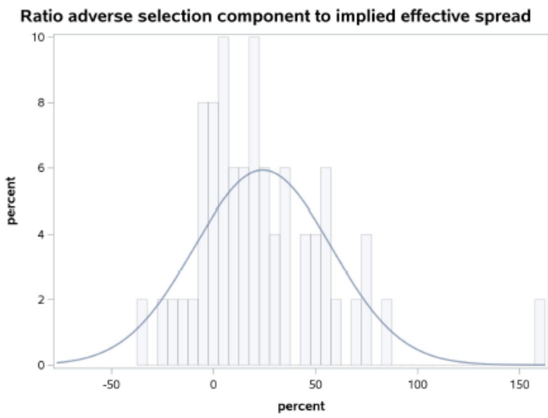
	Mean		*Std.Dev.*		Paired t-Test
	before	after	before	after	P
s_Q	1.858	2.710	1.918	2.407	<0.01%
$r_{Q,Data}$	25.029	36.012	10.601	9.584	<0.01%
s_E	1.155	1.669	1.146	1.534	<0.01%
$r_{E,Data}$	85.549	119.935	24.112	21.304	<0.01%
r_{Adv}	16.670	46.138	21.773	10.869	<0.01%

Note. This table presents model-implied estimated Glosten-Harris spreads and spread ratios before and after the implementation of MiFID II from October 1st, 2017, to March 31st, 2018. The mean $\overline{\hat{s}_i}$ / $\overline{\hat{r}_i}$ and the estimator of the variance across the sample $\hat{\sigma}_{\overline{\hat{s}_i}}$ / $\hat{\sigma}_{\overline{\hat{r}_i}}$ are reported in cents for the quoted spread s_Q and the effective spread s_E. The shares of implied to observed spread $r_{Q,Data}$ and $r_{E,Data}$ and the share of implied spread attributable to adverse selection r_{Adv} are denoted in percent. P-values for the paired t-test on difference in means before and after the MiFID II implementation are given in percent.

7.3 Graphics


Implied quoted spread
percent
0
5
10
15
20
-2
0
2
4
cent


Implied effective spread
percent
0
5
10
15
-2
-1
0
1
2
3
cent


Ratio adverse selection component to implied effective spread
percent
0
2
4
6
8
10
-50
0
50
100
150
percent

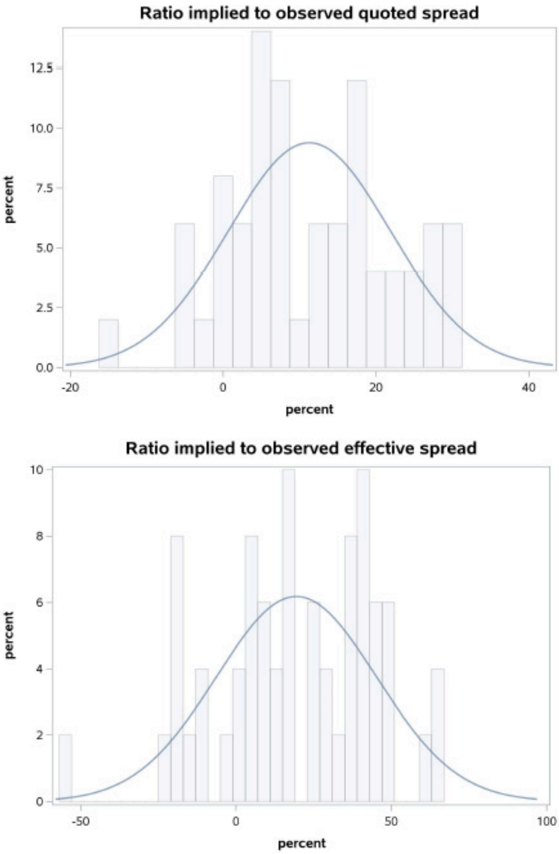
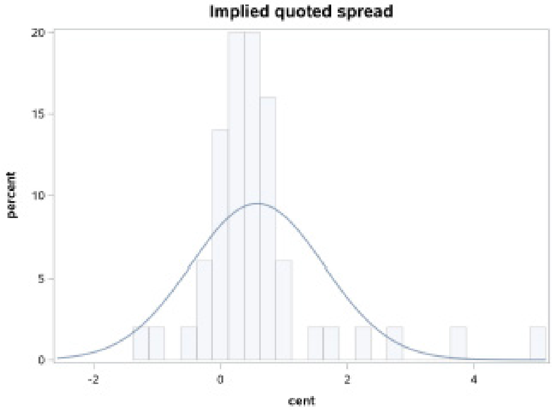
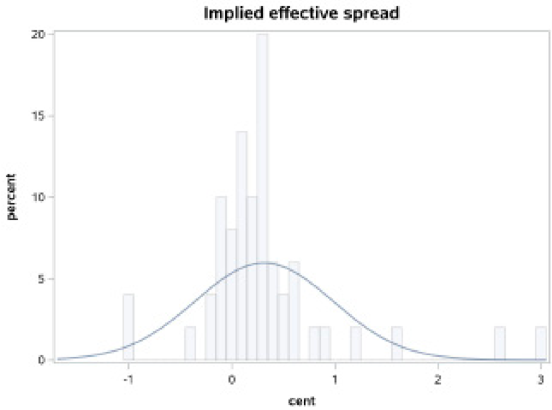
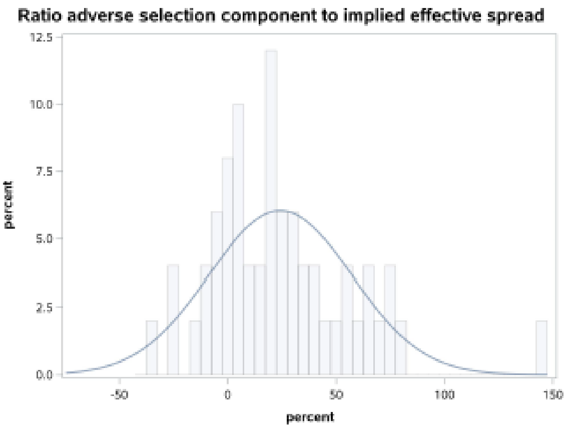


Figure 3: Difference distribution of estimated spread means (Madhavan et al., Dec. 2017 - Jan. 2018)

Note. These figures show the distribution of the individual security differences in mean for the following variables: implied quoted spread s_Q, share of implied quoted to observed quoted spread $r_{Q,Data}$, implied effective spread s_E, share of implied effective to observed effective spread $r_{E,Data}$ and share of implied spread attributable to adverse selection $r_{Adv,E}$. The assumption of normally distributed differences is necessary for the paired t-test and might be violated since most differences display a higher kurtosis than the normal distribution.


Implied quoted spread
percent
0
5
10
15
20
-2
0
2
4
cent


Implied effective spread
percent
0
5
10
15
20
-1
0
1
2
3
cent


Ratio adverse selection component to implied effective spread
percent
0.0
2.5
5.0
7.5
10.0
12.5
-50
0
50
100
150
percent

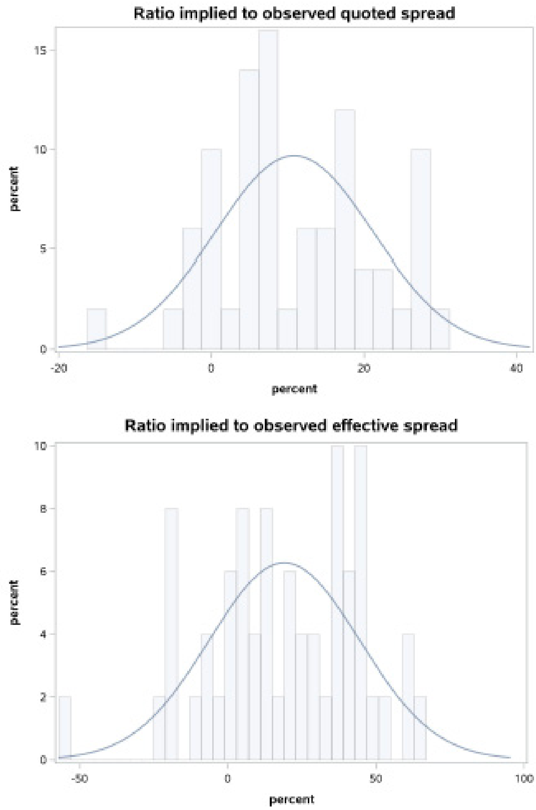


Figure 4: Difference distribution of estimated spread means (Glosten-Harris, Dec. 2017 - Jan. 2018)

Note. These figures show the distribution of the individual security differences in mean for the following variables: implied quoted spread s_Q, share of implied quoted to observed quoted spread $r_{Q,Data}$, implied effective spread s_E, share of implied effective to observed effective spread $r_{E,Data}$ and the share of implied spread attributable to adverse selection $r_{Adv,E}$. The assumption of normally distributed differences is necessary for the paired t-test and might be violated since most differences display a higher kurtosis than the normal distribution.

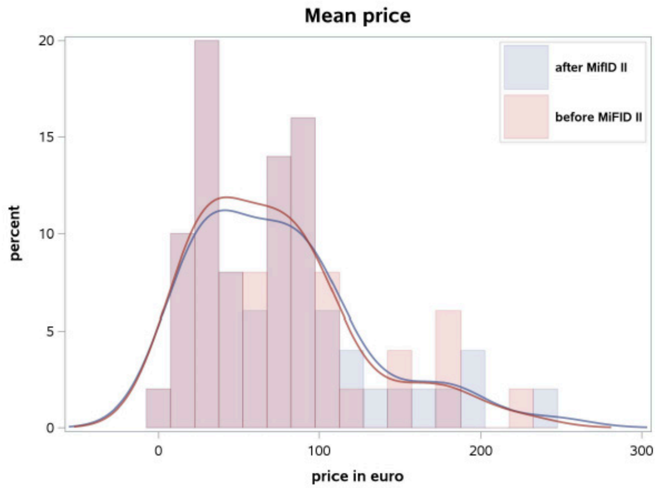


Figure 5: Histogram of prices

Note. This histogram shows the distribution of mean security prices from December 1st, 2017, to January 31st, 2018. The kernel density curve and bars are colored red for the distribution before and blue for the distribution after the implementation of MiFID II.

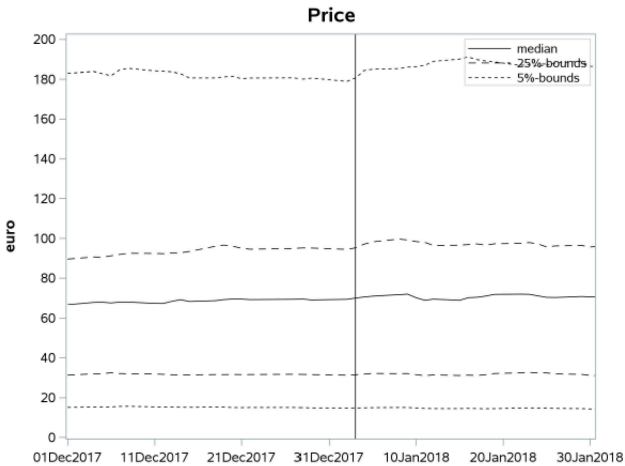


Figure 6: Time series of prices

Note. This figure shows the development and distribution of daily mean prices from December 1st, 2017, to January 31st, 2018. The vertical line displays the MiFID II implementation date.

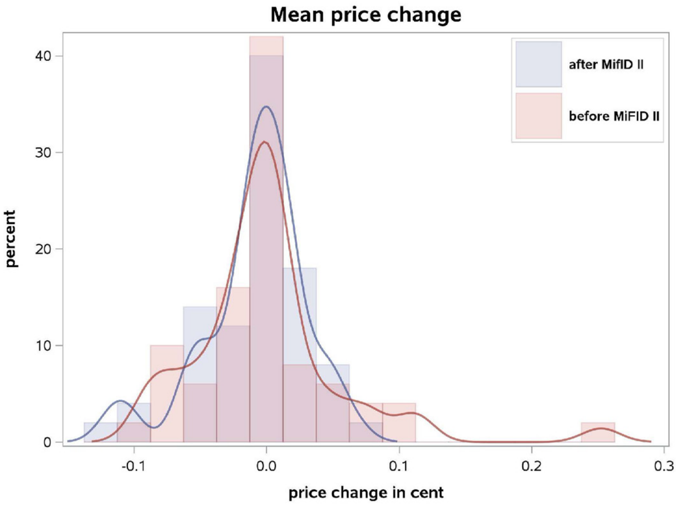


Figure 7: Histogram of price changes

Note. This histogram shows the distribution of mean security price changes from December 1st, 2017, to January 31st, 2018. The kernel density curve and bars are colored red for the distribution before and blue for the distribution after the implementation of MiFID II.

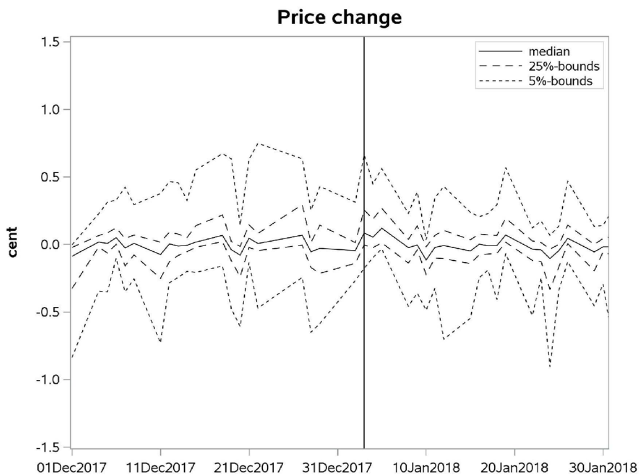


Figure 8: Time series of price changes

Note. This figure shows the development and distribution of daily mean price changes from December 1st, 2017, to January 31st, 2018. The vertical line displays the MiFID II implementation date.

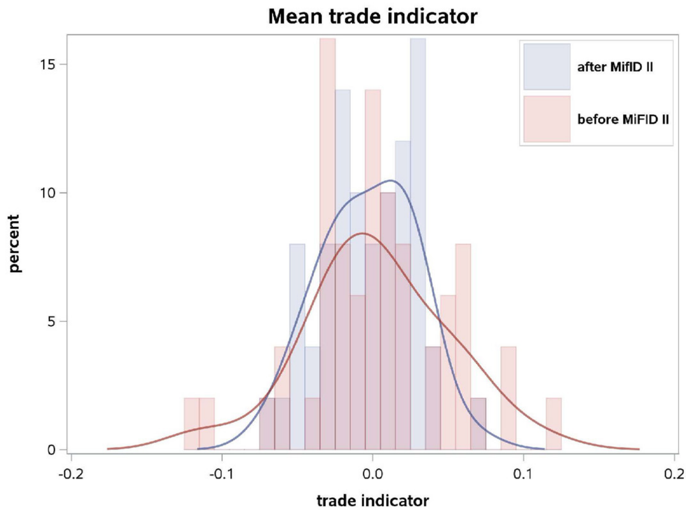


Figure 9: Histogram of trade indicators

Note. This histogram shows the distribution of mean trade indicators from December 1st, 2017, to January 31st, 2018. The kernel density curve and bars are colored red for the distribution before and blue for the distribution after the implementation of MiFID II. A value of 0 can be interpreted as equal number of buys and sells.

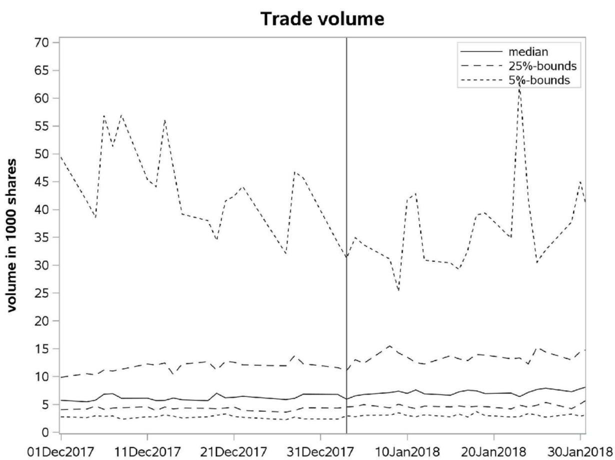


Figure 10: Time series of trade indicators

Note. This figure shows the development and distribution of daily mean trade indicators from December 1st, 2017, to January 31st, 2018. The vertical line displays the MiFID II implementation date. The vertical line displays the MiFID II implementation date.

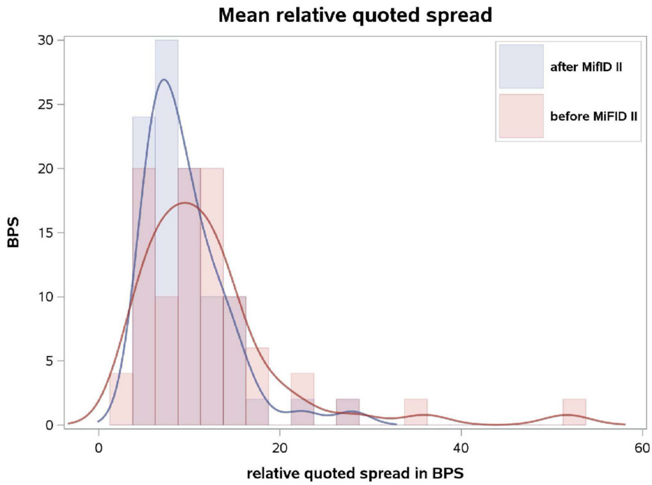


Figure 11: Histogram of trade volumes

Note. This histogram shows the distribution of mean trade volumes from December 1st, 2017, to January 31st, 2018. The kernel density curve and bars are colored red for the distribution before and blue for the distribution after the implementation of MiFID II. The skewness of trade volume is amplified by the trade aggregation process which adds up volumes of multiple trades in one second.

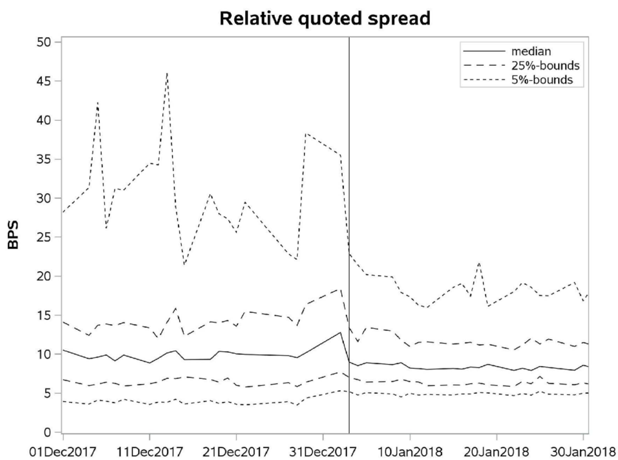


Figure 12: Time series of trade volumes

Note. This figure shows the development and distribution of daily mean trade volumes from December 1st, 2017, to January 31st, 2018. The vertical line displays the MiFID II implementation date.

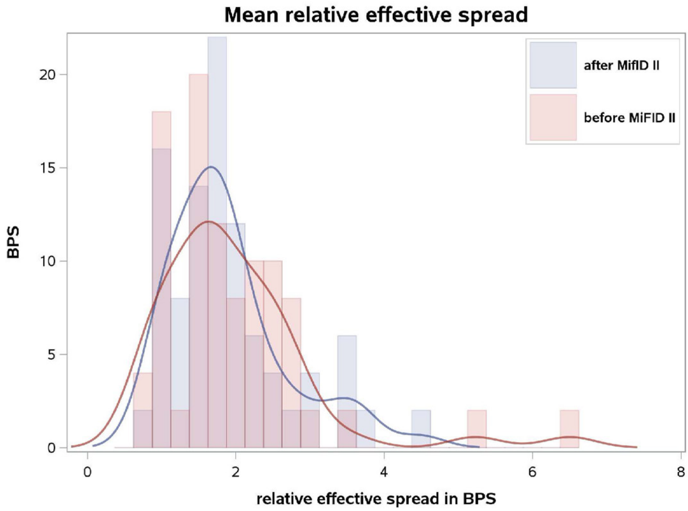


Figure 13: Histogram of relative quoted spreads

Note. This histogram shows the distribution of mean relative quoted spreads from December 1st, 2017, to January 31st, 2018. The kernel density curve and bars are colored red for the distribution before and blue for the distribution after the implementation of MiFID II.

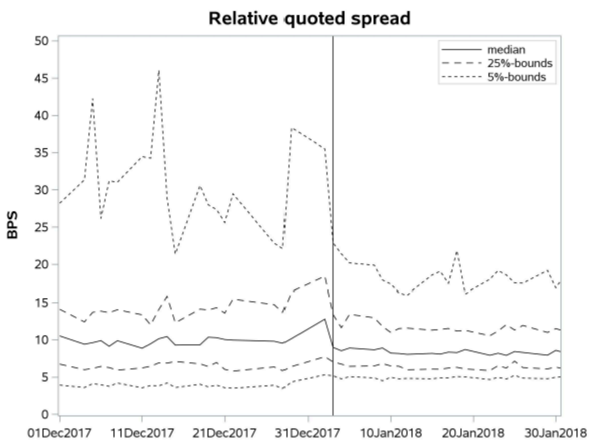


Figure 14: Time series of relative quoted spreads

Note. This figure shows the development and distribution of daily mean relative quoted spreads from December 1st, 2017, to January 31st, 2018. The vertical line displays the MiFID II implementation date.

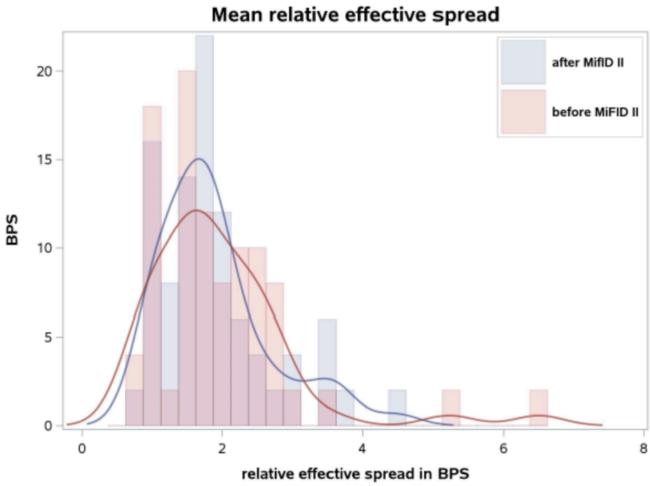


Figure 15: Histogram of relative effective spreads

Note. This histogram shows the distribution of mean relative effective spreads from December 1st, 2017, to January 31st, 2018. The kernel density curve and bars are colored red for the distribution before and blue for the distribution after the implementation of MiFID II.

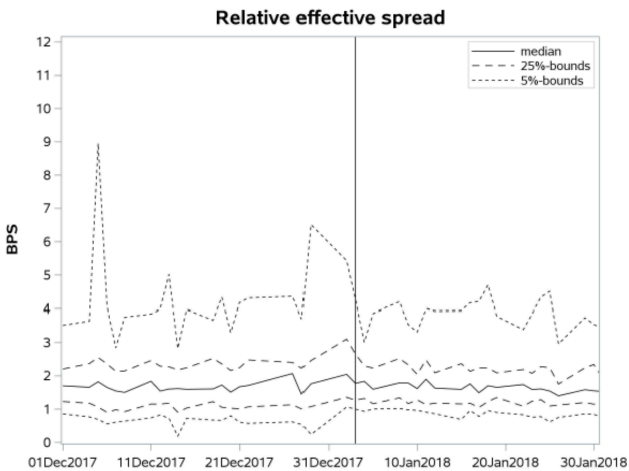


Figure 16: Time series of relative effective spreads

Note. This figure shows the development and distribution of daily mean relative effective spreads from December 1st, 2017, to January 31st, 2018. The vertical line displays the MiFID II implementation date.

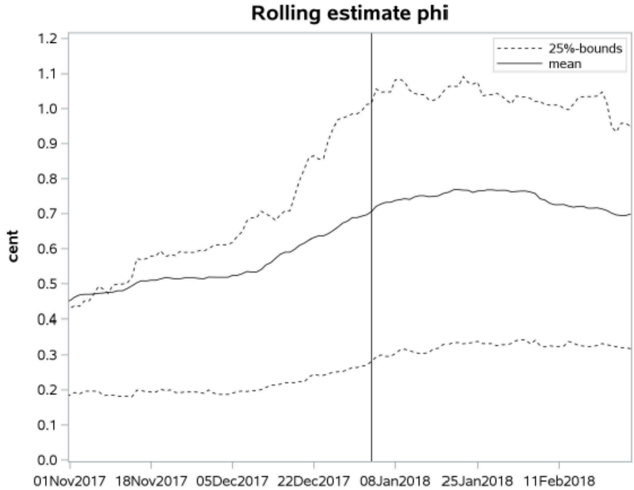


Figure 17: Time series of relative effective spreads

Note. This figure shows the development and distribution of daily mean relative effective spreads from December 1st, 2017, to January 31st, 2018. The vertical line displays the MiFID II implementation date.

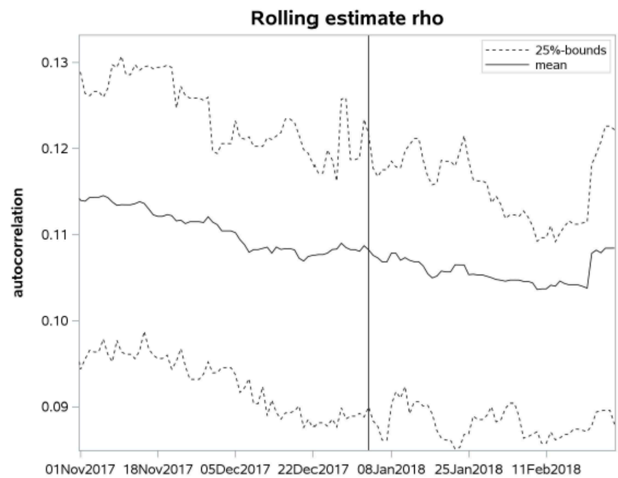


Figure 18: Rolling parameter estimate $\hat{\rho}$

Note. This gure plots the mean estimated Madhavan et al. parameter $\hat{\rho}$ for event dates from November to February with a two months estimation time frame. Starting from the event date, the additional adverse selection parameter is active. The vertical line displays the MiFID II implementation date.

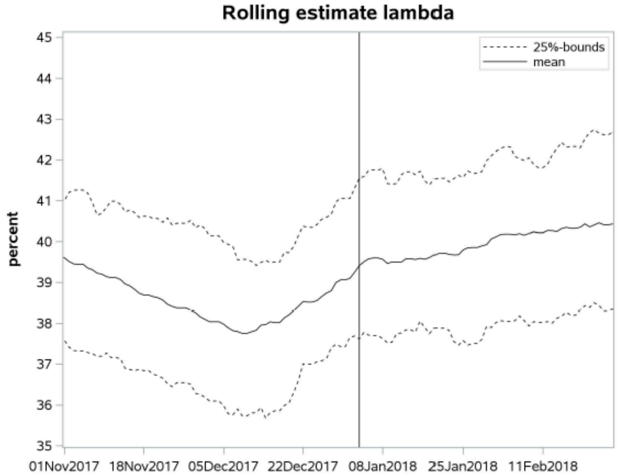


Figure 19: Rolling parameter estimate $\hat{\lambda}$

Note. This figure plots the mean estimated Madhavan et al. parameter $\hat{\lambda}$ for event dates from November to February with a two months es- timation time frame. Starting from the event date, the additional adverse selection parameter is active. The vertical line displays the MiFID II implementation date.

$\hat{\lambda}$

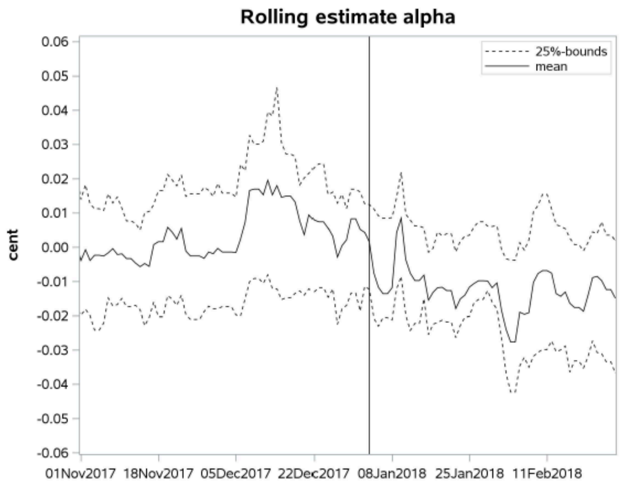


Figure 20: Rolling parameter estimate $\hat{\alpha}$

Note. This figure plots the mean estimated Madhavan et al. parameter $\hat{\alpha}$ for event dates from November to February with a two months es- timation time frame. Starting from the event date, the additional adverse selection parameter is active. The vertical line displays the MiFID II implementation date.

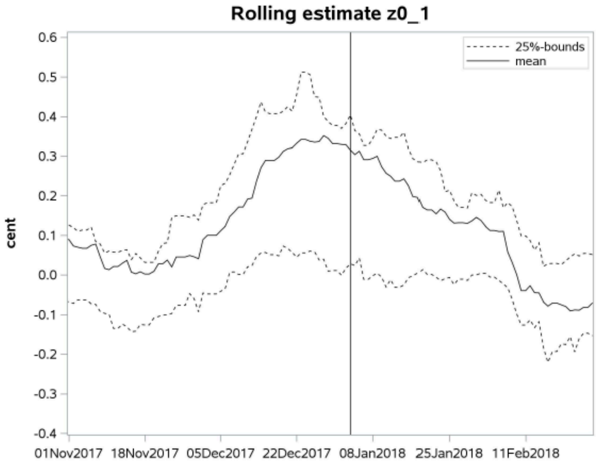


Figure 21: Rolling parameter estimate $\hat{z}_{0_1}$

Note. This figure plots the mean estimated Madhavan et al. parameter $\hat{z}_{0_1}$ for event dates from November to February with a two months es- timation time frame. Starting from the event date, the additional adverse selection parameters are active. The vertical line displays the MiFID II implementation date.

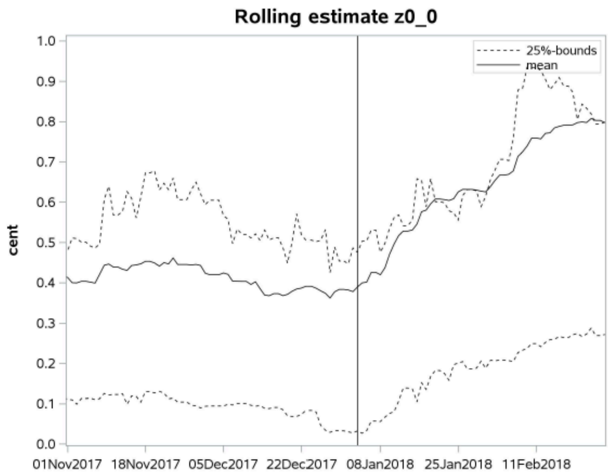


Figure 22: Rolling parameter estimate $\hat{z}_{0,0}$

Note. This figure plots the mean estimated Madhavan et al. parameter $\hat{z}_{0,0}$ for event dates from November to February with a two months es- timation time frame. Starting from the event date, the additional adverse selection parameters are active. The vertical line displays the MiFID II implementation date.

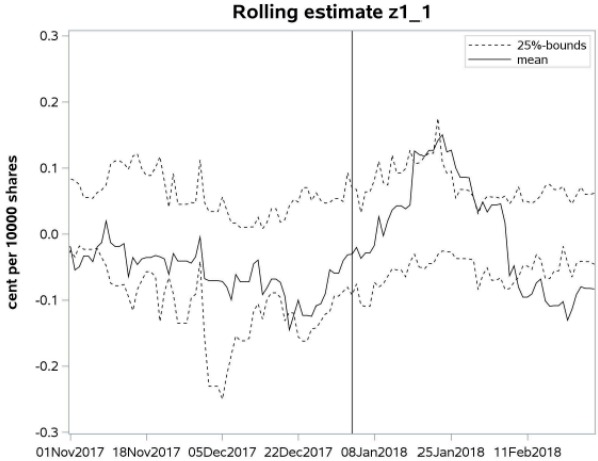


Figure 23: Rolling parameter estimate $\hat{z}_{1,1}$

Note. This figure plots the mean estimated Madhavan et al. parameter $\hat{z}_{1,1}$ per 10000 shares for event dates from November to February with a two months estimation time frame. Starting from the event date, the additional adverse selection parameters are active. The vertical line displays the MiFID II implementation date.

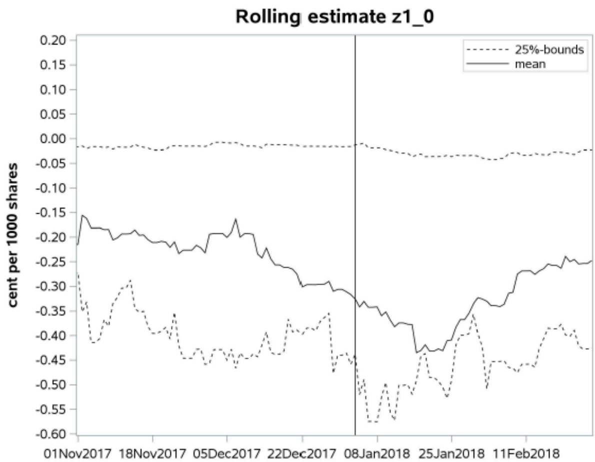


Figure 24: Rolling parameter estimate $\hat{z}_{1,0}$

Note. This figure plots the mean estimated Madhavan et al. parameter $\hat{z}_{1,0}$ per 10000 shares for event dates from November to February with a two months estimation time frame. Starting from the event date, the additional adverse selection parameters are active. The vertical line displays the MiFID II implementation date.

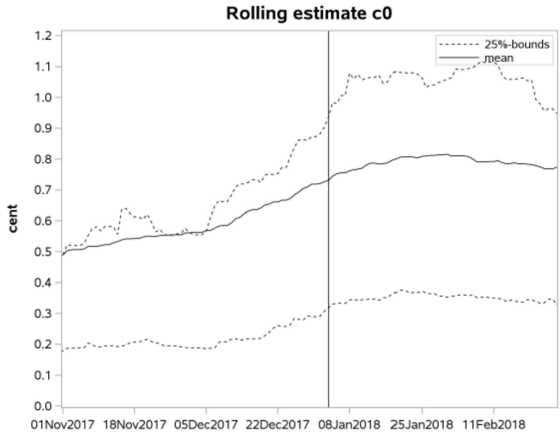


Figure 25: Rolling parameter estimate ˆ co

Note. This figure plots the mean estimated Madhavan et al. parameter ˆ co for event dates from November to February with a two months estimation time frame. Starting from the event date, the additional adverse selection parameters are active. The vertical line displays the MiFID II implementation date.

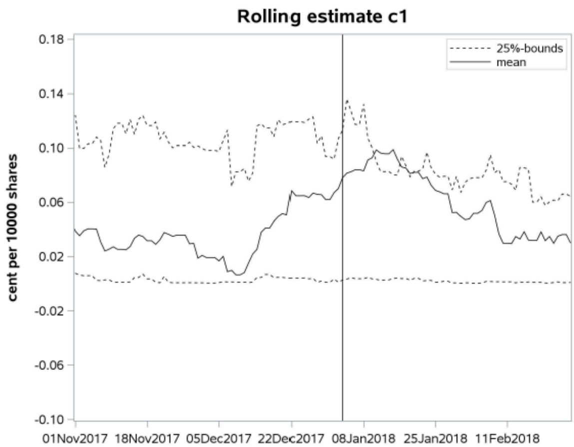


Figure 26: Rolling parameter estimate ˆ c1

Note. This figure plots the mean estimated Madhavan et al. parameter $\hat{c}_1$ per 10000 shares for event dates from November to February with a two months estimation time frame. Starting from the event date, the additional adverse selection parameters are active. The vertical line displays the MiFID II implementation date.

8 Works Cited

Yakov Amihud and Haim Mendelson. Trading mechanisms and stock returns: An empirical investigation. Journal of Finance, 42(3):533{53, 1987.

Autorite des Marches Financiers. Mid ii: Impacts of the new tick size regime. Autorite des Marches Financiers: Risk and Trends, 2018.

Lars Boyde, Sue Yang, Tom Campbell, and Neal Naidoo. Order book liquidity on primary markets post mid ii. Deutsche Bank, 2018.

Cboe European Equities. Cboe european equities website. https://markets.cboe.com/europe/equities/overview/, 2019a. Accessed: 2019-01-04.

Cboe European Equities. Cboe european equities participant manual draft march 2019. https://cdn.cboe.com/resources/participant_resources/CboeEE_EU_ParticipantManual.pdf, 2019b. Accessed: 2019-01-04.

European Parliament and Council of the European Union. Directive 2014/65/eu on markets in nancial instruments. Ocial Journal of the European Union, https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32014L0065&from=DE, 2014. Accessed: 2019-01-04.

European Securities and Market Authority. European securities and market authority website. https://www.esma.europa.eu/policy-rules/mifid-ii-and-mifir, 2019. Accessed: 2019-01-04.

Stefan Frey and Joachim Grammig. Liquidity supply and adverse selection in a pure limit order book market. Empirical Economics, 30(4):1007{1033, 2006.

Lawrence R Glosten and Lawrence E Harris. Estimating the components of the bid/ask spread. Journal of Financial Economics, 21(1):123 { 142, 1988.

W.H. Greene. Econometric Analysis. Prentice Hall, 2003.

Lars Hansen. Large sample properties of generalized method of moments estimators. Econometrica, 50(4):1029{54, 1982.

Fumio Hayashi. Econometrics. Princeton Univ. Press, Princeton, NJ [u.a.], 2000.

Roger D Huang and Hans Stoll. The components of the bid-ask spread: A general approach. Review of Financial Studies, 10(4):995{1034, 1997.

Charles Lee and Mark Ready. Inferring trade direction from intraday data. Journal of Finance, 46(2):733{46, 1991.

Ananth Madhavan, Matthew Richardson, and Mark Roomans. Why do security prices change? a transaction-level analysis of nyse stocks. The Review of Financial Studies, 10(4):1035{1064, 1997.

Bonnie F. Van Ness, Robert A. Van Ness, and Richard S. Warr. How well do adverse selection components measure adverse selection? Financial Management, 30(3):77{98, 2001. Netfonds. Netfonds website. https://www.netfonds.no/, 2018. Accessed: 2018-11-05.

Richard Roll. A simple implicit measure of the eective bid-ask spread in an ecient market. Journal of Finance, 39(4):1127{39, 1984.

Erik Theissen and Lars Simon Zehnder. Estimation of trading costs: Trade indicator models revisited. CFR Working Paper 14-09, working paper, Cologne, 2014.

Athanasios Verousis, Pietro Perotti, and Georgios Sermpinis. One size ts all? high frequency trading, tick size changes and the implications for exchanges: Market quality and market structure considerations. Review of Quantitative Finance and Accounting, 50(2):353{392, 2 2018.

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