The Effect of Advisors' Incentives on Clients' Investments*

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Abstract

We use granular data from an investment firm and a credible identification strategy to estimate the effect of financial advisors' incentives on client investments. Exploiting a natural experiment triggered by the 2018 implementation of MiFID II, we find that clients' investments respond strongly to changes in advisor incentives. Advisors react through multiple mechanisms: (a) inducing existing clients to bring in new money, (b) channeling it to high-incentive funds, and (c) attracting more new clients. We also find that the MiFID II reform generated more balanced incentives, which translated into higher portfolio efficiency through both lower average fees and stronger portfolio diversification.

JEL *classification*: D81, D91, G40, I23, J24.

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1 Introduction

Many households use financial advisors to help them choose investment products.[1] In the last twenty years, governments around the world have introduced reforms to tightly regulate the relation between advisors and their clients, and the compensation structures that advisors are incentivised with.[2] These reforms have been motivated by the notion that compensation in the form of seller commissions makes advisors favour certain products over others and introduces large distortions in their clients' investment choices. A large body of work has provided evidence in support of this notion, showing for instance that clients relying on advice often hold worse portfolios than self-directed clients (Hackethal et al., 2010).

Because the focus of proposed regulation is typically on how advisors get paid (Reuter and Schoar, 2024), it is unfortunate that existing literature has lacked access to individual advisors' compensation contracts. Yet, without linking these contracts to clients investments, it is difficult to gain a complete picture of the effects of interest. It is impossible, for instance, to estimate elasticities (i.e. how much changes in advisor compensation translate into changes in their clients' investments), and therefore to use these elasticities to evaluate which types of clients will react more strongly to policy-induced changes in incentives. The lack of detailed micro data also makes it difficult to study the mechanisms through which advisors and clients adjust their behaviour in response to changes in advisor compensation. Lastly, linking contracts to investments is necessary to compare the likely client investment returns associated with different contractual arrangements.

In this paper we tackle these questions by leveraging access to the internal administrative records of a medium-sized Spanish investment firm. Our firm manages a large number of active mutual funds, each associated with a different investment style and management fee charged to the client. These funds are marketed through a network of financial advisors who maintain exclusive long-term relations with their clients. Using the firm records, we can compute the investment stocks and flows by each client in each fund managed by the firm between 2015 and 2020. Critically, we can also measure the

[1]Hung et al. (2008) report, for instance, that 73% of US individual investors had contacted a financial advisor before making investment decisions. In the EU, Chater et al. (2010) find that 58% of buyers of investment products report having been influenced by a financial advisor.

[2]For instance, the UK's 2013 Retail Distribution Review banned all advisors from receiving commissions from the sellers of financial products. In the US, the Dodd-Frank Act of 2010 extended the circumstances under which advisors are subject to the fiduciary standard, which typically requires them to be paid by the buyer (rather than the seller) of the financial product.

compensation received by the client's advisor from each fund, which in our firm takes the form of a trailer fee (i.e. a share of the fund's management fee that is charged every month to the client).

To identify the effects of changes in advisor compensation, we leverage a natural experiment triggered by the introduction of the set of European Union-wide regulations known as MiFID II. This comprehensive regulatory reform was introduced in 2018 to enhance investor protection and transparency in financial markets. For historical reasons detailed in Section 2, the share received by advisors (and therefore the trailer fee) varied prior to 2018 both across advisors and (within advisors) across funds. In responding to MiFID II and with the objective of reducing conflicts of interest, the firm adopted in January 2018 a rigid compensation policy which equalised the shares both across advisors and across funds, thereby generating arguably exogenous within-advisor-fund time variation in trailer fees.[3] This variation forms the basis of a generalised differences-in-differences-in-differences (DiDiD) strategy which produces plausibly causal estimates.

We start the empirical analysis by exploiting the aforementioned natural experiment to estimate the effects of trailer fees on the investments of *existing* clients (i.e. clients that were active in the firm both before and after 2018). Using a panel of clients, funds, and months, our DiDiD strategy exploits time variation in fees while controlling for all pairwise interactions of the three panel dimensions. The baseline finding here is that a 10% increase in the advisor's trailer fee from a fund increases the client's investment stock in that fund by 4.6%. The credibility of the DiDiD design hinges on the assumption that no other factor correlated with the change in the trailer fee induced clients to alter their investment choices. To evaluate the validity of this assumption, we interact the change in trailer fees with a set of leads and lags around the introduction of the new policy. We find that the lead estimates exhibit a broadly flat trend prior to this introduction, which provides support for the identification strategy. The lagged estimates are informative in their own right, as they indicate that the adjustment of investment to the new incentives starts immediately and takes place over twelve months.

An important contribution of our paper is to investigate the mechanisms behind the above adjustment. We distinguish between three instances in which advisors could induce

[3] It is important to note that, because the management fees continued to differ across funds, equalising the shares did not equalise the trailer fees across funds. Therefore, the new policy did not create fully balanced incentives, and a conflict of interest remained (although we show that in a significantly weaker form). We detail the rationale for this policy in Section 2. We argue there also that no other change in the relation between advisors and clients was introduced discontinuously in January 2018.

choices geared towards their high-incentive funds: (a) when clients are bringing new money into their portfolio of investments in the firm's funds, (b) when clients are taking money out, and (c) when clients are reallocating their capital across funds but within their overall fund portfolio. We find support for the first mechanism: clients bringing new money in to the firm disproportionally allocated it to the funds in which their advisors received a higher trailer fee (relative to the fee prior to 2018). On the other hand, clients did not reallocate existing investment across funds to suit the incentives of their advisors.

The finding that the treatment effects of incentives are larger for 'new' money suggests that the effects could be much larger for new clients (which, by definition, are bringing new money into the firm), relative to existing clients (which may or may not be bringing new money). We again use the natural experiment described above and estimate for new clients an elasticity between trailer fees and investments of 150%. The finding that the elasticity is three times larger for new clients than for existing clients supports the notion that advisors' influence is highest when the client is bringing new money into the portfolio. It also suggests that the aggregate effects of any policy-induced change in incentives is likely to be higher when advisor-client relations form and break more frequently in the economy.

Next, we investigate additional margins through which advisors adjust their behaviour following the change in incentives. We find that advisors with large changes in incentives: (a) induced their existing clients to bring more money into the portfolio held by the firm, and (b) exerted more effort to attract new clients. Overall, these findings provide a consistent picture of the levers that advisors use (and the constraints that they face) in trying to maximise their compensation when faced with a change in their contracts. Namely, advisors try to get their existing clients to invest in their newly preferred funds, but find that they can only do so when these clients bring new money into the firm. As a result, advisors with large changes in their incentive schemes exert effort to convince their clients to bring new money. New clients can be more easily directed to the advisors' newly preferred funds, so advisors with high changes in incentives exert more effort to attract them.

We conclude the paper by examining whether the 2018 change in incentives translated into more efficient portfolio investments. We find that the Sharpe ratios of the new clients' portfolios increased after 2018, and that this increase was larger for the advisors that experienced a movement towards more balanced incentives. We identify two mechanisms accounting for the improvement in Sharpe ratios. First, the new incentive scheme led advisors to suggest funds with lower fees, thereby increasing returns. Second, the investments became more varied, which led to more diversified portfolios. Overall, this evidence suggests that the change in incentives caused by the introduction of MiFID II was beneficial to the clients in our firm.

While our primary focus is on advisor incentives, our findings also shed light on the broader effects of MiFID II, which represented a major regulatory shift aimed at improving investor protection and reducing conflicts of interest in financial markets. Our results provide evidence on how this regulatory change shaped advisor-client interactions and investment outcomes.

A growing body of evidence has documented that retail investors often display lower financial literacy than would be ideal to make competent investment decisions by themselves (Lusardi and Mitchell 2011, 2014; Hastings et al. 2013). Additionally, advisors can provide general benefits such as decreasing perceptions of risk (Gennaioli et al. 2015). Because of this, regulators have typically targeted advisor compensation while continuing to encourage access to financial advisors. This paper shows that it is possible to yield improvements in investment strategies within a client-advisor relation by targeting advisors' compensation contracts.

However, we note that our findings are subject to caveats regarding external validity. The richness of our analysis stems from the focus on a single, medium-sized, investment firm, for which we have gathered uniquely precise data and engaged with local partners to understand the institutional environment in detail. Leveraging this granular focus is in the tradition of 'insider econometrics' studies (Bandiera et al. 2011, Ichniowski and Shaw 2013) but, as with any study in this tradition, an important question is the extent to which the findings extend to other settings. For instance, the advisors in our firm seem to earn relatively little money, suggesting that they may have other sources of earnings. This means that, to the extent that advisors working on a more full-time basis may behave differently, our results will not necessarily extend to them. We hope that future work, hopefully using larger multi-firm datasets, will examine whether the insights uncovered here are also present in other contexts.

Related Literature Our main contribution is to the large literature studying conflicts of interest in investment advice (Inderst and Ottaviani, 2012a). This literature has used a variety of settings and empirical strategies to argue the presence of misaligned incentives. One early strand of work compares financial products in terms of how much their distribution relies on advisors. Bergstresser et al. (2009) show that broker-sold mutual funds underperform funds that are sold directly to the public. Christoffersen et al. (2013) further find that, within broker-sold funds, those with higher advisor commissions both underperform more and have higher investment inflows. This comparison is even starker in Egan (2019), who studies simple products (i.e. one-year reverse convertible bonds) that can be unequivocally ranked against each other. Again, Egan (2019) finds that products with higher advisor commissions have higher sales despite being unequivocally worse. The overall finding that strongly incentivised products are worse for clients suggests that the advisors recommending these products are likely conflicted.

Studies at the product level are silent on who the advisors are, and their actual recommendations. Another strand of the literature examines directly these recommendations, made to trained actors approaching advisors under a variety of (fabricated) portfolios. Consistently with the literature at the product level, the audit studies of Mullainathan et al. (2012) and Anagol et al. (2017) find that advisors recommend products that are better for them, as opposed to their clients.

The two types of studies above do not analyse who the clients of advisor-sold funds are, and how these clients would have invested in the absence of access to advice. A third branch of the literature tackles these questions by analysing account-level data in banks in which clients have access to financial advice and may or may not use it. Hackethal et al. (2010) and Hackethal et al. (2012) find that advised clients trade more, buy more expensive products and perform worse than self-managed clients. Hoechle et al. (2018) show that this behaviour translates into higher profitability for the bank. Of course, the choice to rely on advisors might be correlated with client unobservables, such as the willingness to acquire exotic products. Chalmers and Reuter (2020) make progress in this respect by studying a defined contribution retirement plan that in 2007 switched from an investment provider offering advice to another provider with which advice was not available (but a high quality default plan was). This switch generated a high number of reluctantly self-directed investors and Chalmers and Reuter (2020) find that the accounts of these investors performed better than they would have if they still had had access to advice.

Our findings confirm the overall literature finding that advisors recommend (and clients purchase) products with higher commissions, as opposed to products more suitable for clients. However, our empirical setting differs from previous studies on misaligned incentives in that we can observe which individual advisor is advising which client and measure granularly the incentives that each advisor receives on each product. Together with our ability to exploit credibly exogenous variation in these incentives, this allow us to expand our understanding of the distortions in advice in three directions.

First, we are the first to calculate the elasticities directly linking commissions to investments *within the same client-advisor pair*. While previous work has for instance compared clients or products with and without advisors, we hold the advisory relation constant and measure how much clients change their investments *as a response* to a change in their advisor's incentives. We can further evaluate the effect that this change has on the performance and associated welfare of the client portfolio. These are important inputs for any policy proposal seeking to reduce misalignment of incentives while maintaining access to professional advice (Reuter and Schoar, 2024).[4] The focus in this paper on the client-advisor relation creates a link with work examining the effect of advisors on their clients investments (Foerster et al. 2017, Stolper and Walter 2019 and Linnainmaa et al 2021). We of course differ from this work on our emphasis on the specific effect of advisor incentives.

Second, the focus on the advisor-client relation allow us to examine the mechanisms through which advisors induce their preferred investments. The main insight here is that advisors find it difficult to reassign clients' investments when the overall amount of investment is not growing in size. By contrast, advisors find it easier to induce investments into their newly incentivised products when clients are bringing new money to be managed. An implication of this is that advisors are more successful influencing new clients than existing clients, as new clients are by definition bringing in new money to the firm.

Third, the ability to track advisors over time further allows us to study other dimensions of their reactions to changes in incentives, such as whether they exert more effort in encouraging new investment from existing clients or in attracting new clients. We argue that these additional effects are consistent with the above mechanism of new money facilitating the reallocation of induced investment.

Plan Section 2 describes the institutional setting and briefly discusses the data. In Section 3 we study treatment effects of incentives on existing and new clients and analyse

[4]Linnainmaa et al. (2021) show that advisors suffer from several behavioural biases in choosing investment products for themselves. A charitable interpretation of the findings that advised products are worse in the previous literature is that advisors *sincerely* believe that the recommended products are better for their clients. Our finding that advisors swiftly change their product recommendations as their incentives change is inconsistent with this interpretation.

the mechanisms through which these effects take place. In Section 4 we explore additional channels through which advisors alter their behaviour following a change in incentives. In Section 5 we study how the overall efficiency of the clients' portfolios is affected by the advisors' incentives. Section 6 discusses external validity and concludes.

2 Institutional Setting

The data in this paper ranges between January 2015 and December 2020, and it was made available to us under a strict confidentiality agreement. We now describe the setting in which our study takes place. We also discuss some summary statistics of our firm, clients and advisors.

Firm Products and Revenues The firm actively manages a large number of mutual funds (the *internal funds*), on behalf of the participants in these funds. These funds are associated with a variety of investment styles and risk profiles, and include equity funds (benchmarked against various national stock indices), fixed-income funds, as well as balanced funds (that invest in both equity and fixed-income securities). In addition, the firm provides brokerage services. Therefore, the financial products that clients can acquire through the firm include the internal funds, and also products managed by other firms (the *external products*), such as stocks, bonds, investment funds, futures, options, etc. In practice, most clients devote the overwhelming majority of their capital to investing in internal funds.

The firm's *management fee* on the internal funds takes the form of a percentage of the investment held in the fund by the client.[5] These *fee percentages* differ across the funds in our sample, with a typical value of an annual 1.5% and the highest percentage being more than twice the lowest percentage.[6] The fee percentages did not vary across clients or advisors and remained constant throughout our sample period.

[5]Clients using the firm as a broker to transact external products compensate the firm with a one-off *brokerage fee*, at the time of the transaction. Advisors receive a percentage of this brokerage fee, a commission that in our sample period is constant across products, advisors and time. Naturally, clients purchasing external products such as investment funds may also pay periodically to the external asset management firms.

[6]The fee percentages in our firm are independent of the fund's return. There are no front-end loads (a fee paid by investors upon purchase of the financial product) or back-end loads (a fee paid upon sale).

Clients Our samples include a maximum of 6,132 clients. We exclude from the sample 173 clients who are either advisors themselves or are close relatives of advisors. Panel A Table 1 provides client summary statistics. The mean client was born in 1963 and joined the firm in 2007.

As part of MiFID II (the EU law that we discuss below), clients have to fill a Know Your Customer (KYC) questionnaire that is used to evaluate the suitability of the products purchased. We use these answers to measure the financial education, professional links to finance and financial knowledge of the client. Around 10% of clients self-report an income in the top two brackets of the questionnaire (i.e. above €60,000). Unfortunately, the questionnaires are available only for around half of the clients.

The KYC questionnaires also provide information on the gross wealth of the firm clients. Panel A Table 1 provides summary statistics of investment with the firm (mean = €102,062), gross wealth (mean = €504,605) and the percentage of gross wealth invested with the firm (mean = 31%). We can use the Spanish Survey of Household Finances (EFF) 2017 (Banco de Espana, 2019) to evaluate how representative our clients are of mutual funds investors in Spain. We find that our clients have more wealth than the typical Spaniard (mean = €302,260), but less than the 7% of Spaniards that invest positive amounts in mutual funds (mean = €809,376). Our clients invest a higher proportion of their wealth in the firm than the typical mutual fund investor invests in funds (31% versus 11%), despite investing a bit less in absolute terms.[7]

Unfortunately the KYC information on our clients' wealth is cross-sectional (i.e. each client completes the survey at most once) and it is not decomposed into its different wealth subcomponents. As a result, we are unable in our analysis below to study how the share of the financial portfolio invested through other firms is affected by changes in advisor incentives in our firm. We cannot even directly measure what percentage of clients' total financial assets is invested with our firm, although we can use the EFF to provide an estimate of this percentage. To do this, we take observable characteristics of our clients (age, gender, gross wealth, education, and income bracket) and use a random

[7]The comparison is not perfect because we are measuring our clients' investment in *our firm products* (out of which the mean client devotes 76% to the internal funds) with the EFF fund investors investment *in all funds*, regardless of what firm manages these investments. Furthermore, all the means discussed above are highly sensitive to the fact that the distributions are highly right skewed. Because of this, a better comparison would use the medians. The comparisons are similar. Our median client invests through the firm less than Spanish fund investors (€31,315 versus €28,000), has less wealth (€260,000 versus €446,000) and invests a larger proportion of their gross wealth (19% versus 7%). Most importantly, the median client devotes only 9.2% of their investment in the firm to the external products.

forest algorithm to identify comparable EFF investors. Using these EFF investors as the best available comparison group, we can predict that our mean client holds 40% of their wealth in financial assets, and the rest in (typically illiquid) real assets such as their primary home. Therefore, our mean client invests 67% of their financial wealth with our firm.[8] This implies that the decisions that our clients take have economically meaningful effects on their financial wealth, although unfortunately we are not able to observe how the overall wealth depends on the advisor incentives in our firm.

Advisors The firm markets both its internal funds and its brokerage services through a network of financial advisors. These advisors are self-employed but have an exclusive contractual arrangement with the firm. The role of these advisors is to solicit clients, inform them of potential investment opportunities, manage their orders and keep them regularly informed of their portfolio's performance. Advisors are licensed to sell individual securities and derivatives, but they are not subject to a fiduciary duty and cannot engage in discretionary trading on behalf of their clients.[9] An internal company rule specifies that clients first signing with the firm through an advisor will not be transferred to a different advisor, unless the original advisor ceases to work for the firm.[10]

Our samples includes a maximum 166 financial advisors (see Panel C Table 1 for summary statistics). 30% of advisors had acquired an approved financial advisor qualification, such as CISI (Chartered Institute for Securities and Investment) and EFPA (European Financial Planning Association) by December 2020. The average advisor joined the firm in 2007. On average, each advisor serves 41 clients.

Throughout our sample period, advisors were not paid any base wage. Instead, advisors were paid a commission (i.e. a percentage) of the management fee that the firm charged to the client, when the client maintained their investment in an internal fund. A distinctive feature of our setting is the fact that many advisors in our sample earn

[8] We reach a very similar prediction if we take the mean EFF fund investor as a counterfactual for our mean client, instead of relying on the more sophisticated yet slightly opaque random forest algorithm.

[9] Advisors subject to a fiduciary duty are legally bound to act in their clients' best interests. Advisors not subject to a fiduciary duty typically only have to fulfill a 'suitability' obligation. The advisors in our firm resemble the US 'brokers-dealers' more than the US 'registered investment advisors'. We follow existing work in referring to them as 'financial advisors' (see Egan et al. 2019 and Gurun et al. 2021).

[10] We have investigated whether this rule is followed in practice. By decomposing the total number of clients into three groups, we find that: (a) 94.3% do not change advisors at all during our sample period, (b) 4.3% switch to a different advisor when their previous advisor leaves the firm, and (c) 1.4% change advisor but with their previous advisor remaining at the firm. This decomposition indicates that the company rule was followed for the overwhelming majority of clients.

relatively little money. We display in Panel C Table 1 summary statistics for the annual income of the advisors in our sample. The median of €23,000 and the mean of €39,000 are similar to estimates of annual earnings for Spanish financial advisors by Glassdoor (2022).[11] Figure 1 nevertheless implies that a substantial proportion of our sample's advisors are not making a living wage (unless they have additional sources of income). Our findings below therefore need to be interpreted with the caveat that they partly come from advisors that earn relatively little.[12]

Initial Variation in Commissions Prior to 2018 the commissions that the firm paid to advisors differed *both across advisors and across funds.* The main determinant of the value of the commission for an advisor/fund combination was whether the advisor had been hired prior to 2010.

Consider a typical advisor hired before 2010. Prior to 2018, this advisor would receive a relatively high commission in around two thirds of the funds, a lower commission in a quarter of the funds and an even lower commission in the remaining funds.[13] By contrast, a typical advisor hired after 2010 would receive the same commission regardless of the fund where their clients invested their money. Interestingly, the commission received by the pre-2010 advisors was higher in some funds and lower in other funds, relative to the constant-across-funds commission received by the post-2010 advisors. Table 2 provides an illustration of the variation in contractual arrangements in our sample.

The reason for the differential treatment of advisors was as follows. The firm's management decided in 2010 to simplify its compensation policy, and move to a single commission applying to all funds. However, it proved very difficult to renegotiate contracts with existing advisors. As a result, the constant commission applied only to newly hired advisors. Thus, advisors with different contracts worked side by side, depending largely on whether they had joined the firm before or after 2010.[14] This disparity prevailed until

[11] See https://www.glassdoor.es/Sueldos/asesor-financiero-sueldo-SRCH_KO0,17.htm. The mean when accessed on the 28/06/2024 was €38,000, which deflated in to 2018 Euros represents around €32,000.

[12] However, we show in Section 3 that the average client in our dataset has an advisor that earns relatively more than the average advisor. Therefore, our baseline results are based disproportionately on the behaviour of high-earning advisors.

[13] The actual values of these commissions cannot be disclosed for confidentiality reasons. The firm further wishes the number of funds in our dataset to be confidential.

[14] In addition to the 2010 change, other changes were introduced throughout the years. These changes were relatively minor in that they involved only small adjustments in the commission of some funds. The main difference in contracts is between advisors hired before and after 2010.

the introduction of MiFID II in January 2018.[15]

MiFID II The Markets in Financial Instruments Directive II (MiFID II) is a comprehensive set of regulatory reforms introduced by the European Union with the core objective of strengthening investor protection. In terms of advisor incentives, MiFID II continued to allow their compensation to depend on the revenue generated, although it now encouraged firms to provide more balanced incentives across products. It was the introduction of MiFID II that prompted the firm to modify its compensation policy in January 2018, in the way that we describe in the next subsection.

In addition to its implications for incentives, MiFID II contained additional requirements regarding advisory services. These were: (a) increased transparency of charges, (b) the requirement that all advisors acquire approved qualifications within a four-year period, (c) the requirement to keep records of all communications with clients, and (d) formal surveys, to be completed by customers, attesting to the suitability of the advice provided.[16] Importantly for our purposes, these provisions were typically *not* introduced by the firm to discontinuously coincide with the January 2018 change in compensation policy. We discuss the timing of these provisions in more detail in Section 3.

The January 2018 Change in Advisor Incentives MiFID II provided the firm with the impetus to renegotiate existing contracts and homogenise its compensation policy. A core objective of this change was to decrease conflicts of interest between advisors and clients. Specifically, starting in January 2018 all advisors received a commission that was the same both across advisors and across funds. The pre-2018 heterogeneity in commissions implied that a typical post-2010 advisor experienced no change at all in their compensation structure. On the other hand, for pre-2010 advisors the commission increased in some funds while decreasing in others. The change in compensation policy therefore generated time variation in commissions *within advisor/fund*. We illustrate this time variation in commissions in Table 2.

To capture the change on financial incentives, we define the trailer fee as the percentage

[15] The fact that the treatment and control groups in the empirical strategy of Section 3 are linked with the advisor's cohort raises the potential concern that clients of different advisor cohorts might have been differentially changing their investment strategies already prior to January 2018. We show in Section 3 that this was not the case.

[16] MiFID II also required a percentage of the agents' compensation to be based on qualitative components. The firm complied by subjecting advisors to a small deduction in their compensation if they consistently failed to adopt any steps necessary to meet the additional provisions of MiFID II.

of client c's investment in fund j that is paid in month t to their advisor a. We can then write the revenue that the investment of a client in a fund generates for their advisor as:[17]

$$AdvisorRevenue_{cjt} = \underbrace{Commission_{a(c)jt} \times PercentageFee_j}_{TrailerFee_{a(c)jt}} \times Investment_{cjt}$$

The trailer fee is the main independent variable in our study, as it most directly captures an advisor's financial incentive to encourage their client to invest in a fund. Table 2 displays an illustration of how the cross-sectional and time variation in commissions translates into variation in trailer fees.

Four features of the time variation in trailer fees are important to emphasise. First, there was no change in disbursements from the clients' perspective, as the management fees remained constant throughout the sample period. Therefore, any change in client investments coinciding with the change in advisor compensation *cannot* be attributed to a change in the fees paid by the client.

Second, as with the advisor's commission, the trailer fee increased in January 2018 for some advisor/fund combinations, but decreased for others. This is captured by the illustration of Table 2, where we can see that pre-2010 advisors became better paid in some funds and worse paid in other funds.

Third, the fact that in 2018 the commission became constant across both advisors and funds meant that trailer fees continued to differ across funds (due to the differences in management fees), although they ceased to differ across advisors. Therefore, the post-2018 incentives continued to be misaligned, as they continued to favour certain funds over others.

Our last point relates to timing. Advisors were obviously aware of the forthcoming introduction of the MiFID II regulations and likely expected it to affect their incentive contracts. However, the specific form that the new policy took (i.e. equalising the commissions across all funds and advisors) was not determined by the firm and communicated to advisors until the autumn of 2017. Because of this, we can regard the change in compensation policy as largely unanticipated, in that advisors could have foreseen its specific

[17] Throughout the paper, we choose the intermediate subscripts to reflect the variation in the variable and the final subscripts to uniquely define a row in our dataset. In our baseline dataset, a row is uniquely defined by a client/fund/time combination. The variable $Investment_{cjt}$ varies at this level, hence its subscripts. The variable $Commission_{a(c)jt}$ varies at the advisor/fund/time level, but an advisor is uniquely determined by the client's identity, hence $a(c)jt$.

details no more than a quarter prior to January 2018. Consistent with this, we argue in Section 3 below that the observed change in clients' investments broadly coincided with the introduction of the new compensation policy.

3 Effects on the Allocation of Investment Across Funds

In this section, we estimate the causal effect of trailer fees on the allocation of client investment across funds, holding constant the total client investment. Our baseline dataset is a panel dataset at the active client/fund/month level.[18] To be active in a month a client must maintain a positive investment in at least one of the internal funds. Panel D Table 1 displays summary statistics of our baseline panel. The average active client invests in only 19% of the funds. Median investment in a fund is therefore zero, while the mean is around €4,000. There is significant variation in the annual trailer fees, with the mean being around 1% and a standard deviation of .26%.

We first identify this elasticity for existing clients. We then show that the effect operates through the mechanism of clients bringing new money into the firm, and then allocating this new money to funds in which their advisors' receive higher fees. We then confirm the importance of this 'new money' mechanism by showing that the elasticity of trailer fees on fund investments is three times larger for new clients (who by definition are bringing new money into the firm) than for existing clients.

Effects on the Investment Stock of Existing Clients We first study 'existing' clients, that is clients joining the firm before the 2018 change to the compensation scheme, and remaining with the firm for at least one month after that. We use the baseline client/fund/month dataset and exploit the change in compensation policy as a source of plausibly exogenous variation in trailer fees. The equation of interest is a generalised differences-in-differences-in-differences (DiDiD) equation with continuous treatment:

$$Investment_{cjt} = \lambda LogTrailerFee_{a(c)jt} + \eta_{ct} + \kappa_{jt} + \mu_{cj} + \epsilon_{cjt}, \tag{1}$$

[18] Our panel in this section only includes the internal funds managed by the firm, and not the hundreds of additional external products for which the firm acts as a broker and receives no trailer fee. Including these external products in our panel would strongly increase its dimensionality while adding negligible additional variation or insights, given that the average client invests a negligible amount in the average external product. However, we do include the external products in our analysis in Section 5, where we analyse the Sharpe ratios of the overall investment portfolios.

where $Investment_{cjt}$ is the stock of investment by client c in fund j in month t, and $LogTrailerFee_{a(c)jt}$ is the (log of the) trailer fee received by advisor a of client c from fund j in month t.[19][20]

Panel D Table 1 shows that the investment variable takes value zero in a high proportion of observations, while at the same time displaying long right tails. This fact requires caution in the choice of dependent variable in (1). The main dependent variable is the inverse hyperbolic sine transformation (ihst) of the stock of investment.[21] As alternative variables, we also use a positive investment dummy and the share of the investment value in the fund relative to the client's total investment. Standard errors are clustered at the advisor level.

It is important to emphasise that equation (1) includes all three pairwise sets of fixed effects. The inclusion of client/fund indicators implies that the estimate of λ is not contaminated by selection effects, whereby an advisor with a contract including a high trailer fee on a specific fund starts to search for clients who are already predisposed to investing in such a fund. Instead, we follow the same client/fund cell over time and study how investment within this cell varies when the trailer fee of the client's advisor changes. The inclusion of fund/time indicators accounts for any general shocks or trends that may have made certain funds more attractive in certain periods (e.g. any economy-wide move towards low-fee funds). Last, the client/time indicators imply that we must interpret the

[19]Note that our empirical specification is not affected by recent criticisms about DiD designs (de Chaisemartin and D'Haultfœuille 2018, Callaway and Sant'Anna 2021, Goodman-Bacon 2021). First, treatment is not 'fuzzy' as defined in de Chaisemartin and D'Haultfœuille (2018) because no client/fund unit is treated in the control group (defined as all observations related to advisors that joined the firm after 2010). Second, treatment affects all the (treated) advisors simultaneously and they stay treated for the remaining of our sample period. This rules out the concerns related to staggered treatment designs (Callaway and Sant'Anna 2021, Goodman-Bacon 2021). Finally, our parallel trend assumption does not rely on dynamic controls beyond those that define the variation we exploit in our panel (i.e. we don't need to condition on any control that varies at the same level as the treatment variable). Therefore, we can interpret our parallel trend assumption as unconditional, which rules out the concerns described in Callaway and Sant'Anna (2021) for two periods DiD designs.

[20]We use the log of the trailer fee as the independent variable of interest, so that we can interpret the main coefficients as elasticities. See Column 5 Table A1 for a specification in which the trailer fee is in levels.

[21]This transformation has the advantage that it can be used to estimate elasticities (like the log transformation), while also being defined for any real number, most importantly for zero or even negative values (Burbidge et al., 1988). Being defined for negative values implies that we can also use it for the flow of investment. Table A1 shows that the estimates from Column 1 Table 3 are almost identical when instead using the log of investment plus one. Table A1 displays also estimates when: (a) using the dependent and independent variables in levels, and (b) a conditional quasi-maximum likelihood fixed-effect Poisson model, which has been shown to be a good alternative choice when dealing with data with many zeros (Santos Silva and Tenreyro, 2006).

effects in this section as effects on the *allocation* of investment across funds, holding the total investment of a client in a month constant.

Columns 1-3 in Table 3 provide the estimates of (1). The coefficient from Column 1 can be interpreted as an elasticity, and indicates that a 10% increase in the trailer fee (e.g. from 1% to 1.1%) leads to a 4.6% increase in investment. Qualitatively, the finding that clients change their investments as their advisors' incentives change confirms previous literature showing that investment advice is often conflicted. In economic terms, the very large elasticity estimated suggests that any policy-induced changes in advisor incentives are likely to have a quantitatively large impact on the investments of their clients.

We interpret the coefficient in Column 2 as follows: a 10% increase in the trailer fee is associated with a .41 percentage points increase in the likelihood that the client invests in the fund at all (this is 2.3% of the unconditional likelihood, which is 19 percentage points). The coefficient in Column 3 indicates that a 10% increase in the trailer fee leads to a .22 percentage points increase (over a mean of 6 percentage points) in the share of the total investment allocated to that fund. All three estimates are statistically significant.[22]

Effects on the Investment Flows of Existing Clients The finding above that the stock of client investment reacts to the change in advisor incentives prompts the question as to the mechanism by which this adjustment takes place. In this subsection we distinguish and empirically examine three alternative mechanisms. Consider a client whose advisor's trailer fees change in 2018 (remember that the fees that the client pays are unchanged throughout our period). The advisor would benefit from inducing a different allocation of investments, and the question is how and when to induce such a change. One possibility would be to persuade the client to take money out of funds from which the advisor receives a reduced trailer fee, and move that money into funds with an increased fee. Alternatively, the advisor could wait for the client to bring additional investment into the portfolio, and then persuade the client to allocate that investment to funds with an increased fee. Last, the advisor could persuade clients who are anyway taking money out

[22] In Section 2, we mentioned that a large proportion of the advisors in our sample earn relatively little money. To examine whether our baseline estimates are robust to eliminating less successful advisors, we display in Appendix Table A2 the estimates from our baseline regressions after removing advisors earning less than the 30th, 50th, and 70th percentiles, as well as those making less than the Spanish minimum wage. Two conclusions emerge. Firstly, the number of observations dropped is relatively small, since high-earning advisors account for most of the clients in the baseline sample. Secondly, the estimates are broadly comparable with their baseline counterparts in Table 3 (if anything, they are a bit larger). This exercise suggests that our baseline estimates are mostly coming from relatively high-earning advisors.

of their portfolio to disproportionately take it out of funds for which the advisor receives a newly lower fee.

Our dataset includes information on the date and size of the buy/sell transactions by each client on each fund. We use this information to split transactions into three types, depending on whether they represent: (a) 'incoming investment' by the client into the overall portfolio of internal funds, (b) 'outgoing investment', that is, money leaving the portfolio, or (c) 'investment reallocation', that is reallocation of existing investment across funds but within the client's internal fund portfolio.[23] Incoming investment represents 'new money', whereas outgoing investment and investment reallocation are 'old money' that was already in the internal fund portfolio.

We aggregate these transactions at the client/fund/month level and use them as dependent variables in the baseline specification (1). Columns 4-6 Table 3 show that trailer fees affect client behaviour only when the client is bringing new money into their fund portfolio. For these clients, an increase in the trailer fee of a fund of 10% leads to an increase in the flow into the fund of 1.1%. On the other hand, clients who are selling funds to take the money out of the portfolio or to buy other funds are not significantly affected by their advisors' fees.[24] [25] In Column 7 we use as dependent variable in (1) the net inflow (i.e. the sum of all the transactions by a client on a fund during a month, regardless of the transaction type). We find that an elasticity of around 13%. This elasticity is the flow counterpart of the higher stock of investment when the trailer fee is higher that we

[23]To be classified as incoming investment, a transaction must be a buy transaction and not follow any sell transaction in a different fund and in the previous two days. The purpose of this second restriction is to maximise the likelihood that the buy transaction represents 'new money', that is, investment into a fund that comes from outside the client's internal fund portfolio rather than from the sale of other funds. In the same spirit, we classify as outgoing investment any sell transaction that is not followed by a buy transaction in a different fund and within two days in the future. We classify any other transaction as a reallocation transaction. Note that the definitions of incoming and outgoing investments do not take into account the amount transacted and are therefore quite restrictive. Imagine, for instance, that a client sells €1 in Fund A, buys €10,000 the next day in Fund B and does not undertake any additional transaction in that month. We classify both transactions as reallocation transactions, even though it is clear that the second one consists largely of money incoming into the internal fund portfolio.

[24]Clients selling one fund to buy another generate two separate non-zero transactions in the client/fund/time dataset, which could generate concerns about potential 'double counting' of a single action. The finding that the reallocation of existing investment is not affected by trailer fees suggests that this concern does not appear to be empirically salient.

[25]Capital gains taxes could, in principle, favor investing new money over reallocating existing investments. However, in Spain, mutual fund rebalancing is tax-exempt, with taxes only incurred upon withdrawal from the investment fund system. Thus, taxation cannot account for the weaker response of fund reallocation.

find in Column 1.[26]

Dynamic Effects Equation (1) treats all periods on each side of the compensation change equally. In this subsection, we instead allow the effect of the change in trailer fee to vary across the periods leading up to and following the change in incentives. We estimate these dynamic effects by interacting the change in trailer fee with a set of lead and lag indicators.

Our independent variable of interest is a continuous measure of the 2018 positive shock to incentives received by an advisor/fund combination:

$$SHOCK_{a(c)j} = LogPost18TrailerFee_j - LogPre18TrailerFee_{a(c)j}$$

where the subscripts in the definition of $SHOCK_{a(c)j}$ emphasise that the post-2018 trailer fee varies across funds (due to differences in management fees) but not across advisors, while the pre-2018 trailer fee varies across both. To decrease the noise in the estimates, we combine every three months into their corresponding quarter q, to create a dataset at the client/fund/quarter level and estimate:

$$Investment_{cjq} = \sum_{q=1...10}^{12...24} \pi_q \Big(SHOCK_{a(c)j} \times Quarter_q \Big) + \eta_{cq} + \kappa_{jq} + \mu_{cj} + \epsilon_{cjq} \qquad (2)$$

The regression again controls for all three pairwise sets of fixed effects. We use as omitted group the interaction with the third quarter of 2017, to account for the fact that the new compensation scheme was communicated to advisors in the Autumn of 2017. The parameters $\hat{\pi}_1 \ldots \hat{\pi}_{10}$ capture the estimated leads to the compensation overhaul, while $\hat{\pi}_{13} \ldots \hat{\pi}_{24}$ capture the estimated delayed (or lagged) effects. We plot the estimated dynamic effects in Figure 2 (investment stocks) and Figure 3 (investment flows).

Looking at the lead estimates in Panel A Figure 2, there do not seem to be strong

[26] We do not observe household investments outside the firm, which limits our ability to track the specific sources of new money. However, we use the Spanish Survey of Household Finances (EFF) to examine the main financial assets held by funds' investors and the within-household correlations between changes in mutual fund investments and changes in other financial assets. Table A10 suggests that mutual fund investments are most likely financed through reallocations from liquid assets (such as checking accounts and savings deposits) as well as, and to a lesser extent, pension & life insurance products and managed portfolios. Additionally, the estimated within-household elasticity between annual savings (approximated from reported consumption and income) and fund investments is small and statistically insignificant (-0.017), suggesting that a rise in the total savings rate is unlikely to be the main source of new mutual fund investments.

'pre-trends', as the variable $SHOCK_{a(c)j}$ does not appear to correlate with the evolution of the ihst of investment prior to 2018. We reach broadly similar conclusions in Panels B and C, when using the positive investment and the share of total investment as dependent variables. In the bottom rows of Columns 1-3 Table 3, we confirm this conclusion with formal tests of pre-trends (Borusyak et al., 2024), in which we fail to reject that the lead estimates are jointly equal to zero. In Panels A (Incoming Flow) and D (Net Inflow) of Figure 3 there appears to be some visual evidence of pre-trends, although the formal tests of pre-trends in Columns 4 and 7 Table 3 again display non-significant results. Overall we conclude that, consistently with the identification assumption, clients whose advisors would receive an increase in the trailer fee in specific funds did not start to invest in these funds prior to being informed of that increase.

Examining now the lagged estimates, we find sharp discontinuities around Q4 2017 for the incoming flow (Panel A) and net inflow (Panel D) dependent variables of Figure 3. The interpretation is that when advisors learn about their new incentives, they immediately start to divert investment into their newly preferred funds. This flow effect continues for several quarters, although it becomes progressively weaker as time passes. The flow discontinuities from Figure 3 are mirrored in the immediate changes in trend (but gradual adjustment in levels) of the stock variables of Figure 2. We interpret this overall evidence as suggesting that, while clients react immediately, they do not immediately adjust their portfolios to *fully* suit the new incentives of their advisors. Figure 2 further suggests that this gradual move to a new long-run level of investment takes around twelve months. After Q3 2018, investment has stabilised in its new steady state, as the response to the new incentives appears to be complete.

Overall, Figures 2 and 3 reinforce the conclusion that investment is highly responsive to incentives, not only in terms of the overall magnitudes but also in the swiftness of the response.

Discussion of Identification Concerns The identification assumption in (1) is that no trend or contemporaneous shock caused existing clients to modify their investments across funds in a way that is correlated with the January 2018 within advisor/fund change in trailer fees. The previous subsection has displayed evidence consistent with the lack of pre-trends assumption. This implies that any potential confounding factor (in addition to taking place at the within advisor/fund level) should have been timed to precisely coincide with the end of 2017 and beginning of 2018. A potential concern here is that, in addition to encouraging more balanced incentives, MiFID II included additional provisions to regulate the relation between advisors and clients (see Section 2).

Fortunately, the firm's implementation of these additional provisions did not typically coincide with the January 2018 compensation overhaul. One example is the introduction of client surveys to evaluate the suitability of the financial products under consideration. These tests were introduced in a staggered way over several years, without a discontinuity around early 2018.[27]

A second example is the additional qualifications that advisors had to undertake in order to continue working, such as those provided by the CISI (Chartered Institute for Securities and Investment) and EFPA (European Financial Planning Association). MiFID II allowed a four year grace period to obtain these qualifications. Many advisors in our firm already held them prior to January 2018, and others are proceeding to obtain them gradually. Panel C Table 1 shows that 30% of advisors held them in December 2020.

MiFID II also required a record of all communications between advisors and clients. According to the firm, all telephone interactions with clients to or from the firm's premises were already being recorded prior to January 2018. For other interactions the advisors were required to keep a written summary of the conversation.

The gradual introduction of these additional provisions supports a causal interpretation of the baseline estimates for the following reason. If these provisions were confounding the estimates from Table 3, the fact that they were introduced gradually implies that we should not expect a discontinuity in the effect of the change in trailer fee around 2018. Figures 2 and 3, however, displays a sudden change in the evolution of investment around the beginning of 2018, at the time that the incentives (and only the incentives) discontinuously changed.[28]

Note last that the rigid character of the post-2018 compensation policy (i.e. equalising the commission received both across advisors and across funds) reduces the scope for endogeneity and enhances the credibility of the identification assumption. This is, for instance, because it rules out increases in trailer fees narrowly targeted towards advisor/fund combinations in which the clients of an advisor were independently increasing

[27] The number of tests per semester is displayed in Appendix Figure A1.

[28] It is important to note that there were no discontinuous 'demand effects' in January 2018. In other words, January 2018 did not coincide with a surge in investment by the firm clients, potentially induced by the new MiFID II regulatory environment creating increased client trust and a surge in demand for financial products. In Appendix Figures A2 and A3 we display the evolution of total investment and total number of clients over time. We find that there is no discontinuity around January 2018 equivalent to the discontinuity that we find in Figures 2 and 3.

their investments.[29]

Effects on the Initial Investments of New Clients In this subsection, we estimate the effects of incentives on the initial investments of new clients. We restrict the baseline sample to include only clients joining the firm between 2015 and 2020. For these new clients, our focus is on the investments in their first quarter with the firm.

The estimating equation is

$$Investment_{cj} = \phi LogTrailerFee_{a(c)jq(c)} + \beta_c + \kappa_{jq(c)} + \iota_{a(c)j} + \omega_{cj}, \tag{3}$$

where $LogTrailerFee_{a(c)jq(c)}$ is the trailer fee that the advisor a of client c received from fund j in the first quarter $q(c)$ after the client joined the firm. As dependent variables, we use the stock investment variables from Columns 1-3 Table 3, although the focus on clients' first quarter implies that these variables can also be regarded as measures of net inflows.

Note that the empirical model includes every set of fixed effects that can feasibly be included given the structure of the dataset. The client fixed effects control for the total amount of initial investment. The fund/quarter fixed effects control for any firm-wide shock that might have changed the attractiveness of certain funds at particular moments in time (e.g. a general move towards low-fee funds). Most importantly, the inclusion of advisor/fund fixed effects implies that we are comparing the new clients' initial choices during periods in which the same advisor/fund combinations are associated with different trailer fees.

Panel A Table 4 shows that the new clients of an advisor make initial choices strongly geared towards the funds in which that advisor receives a higher compensation *at that point in time*. The estimated effects are substantially larger in magnitude than the equivalent effects for existing clients in Table 3. For instance, the estimated elasticity from Column 1 Table 4 is 149%, more than three times larger than the corresponding elasticity in Column 1 Table 3. The effects on the positive investment likelihood and the share of total investment are approximately twice as large.

A potential caveat in the interpretation of the above estimates is that advisors experi-

[29] In a setting in which changes to the trailer fees are very idiosyncratic, we may worry about the possibility of reverse causality. Advisors with clients likely to invest in Asian funds in the future would have an interest in re-negotiating increases in the commissions received from Asian funds. The rigid nature of the new compensation policy in 2018 rules out this type of reverse causality.

encing a change in compensation might be motivated to seek new clients with preferences that match their new compensation structure. We examine the empirical relevance of this confounding ‘selection’ effect by including interactions between client characteristics and fund fixed effects. In Panel B Table 4 we find that the coefficients are virtually identical after controlling for these interactions. We conclude that our estimates in this section likely capture treatment effects.

The larger elasticities estimated in this table are consistent with the finding in Column 4 Table 3 that advisors affect investments mostly when the client is expanding its internal fund portfolio. This is by definition the case of new clients, so it is reassuring that the effects are larger for them. From a policy perspective, the larger effects for new clients suggest that changes in incentives induced by new regulations will vary in their aggregate effects depending on whether advisor/client relations are very stable over time. Specifically, settings in which relations are stable and clients rarely bring new money into their portfolios (after the initial allocation) will be associated with weak effects of policy. In settings where clients often add new money to their original investments and there is a high turnover of clients across advisors, the effects are likely to be much stronger.

4 Effects on Total Investment and Client Flows

In the previous section we have studied the effect of incentives on the *allocation* of investment across funds, holding constant the total amount of investment by the client. In this section, we instead study the effect of incentives on the *total* flow of investment and new clients that advisors induce in response to a change in incentives.

Effects on the Total Investment Flows of Existing Clients We have shown in the previous section that existing clients rebalance their investments to adjust them to their advisors’ change in compensation *only* when they are bringing new money into the firm. An advisor experiencing a change in compensation structure might therefore have an incentive to persuade their clients to bring new money, so that this money can be allocated to the advisor’s newly preferred funds. In this subsection, we study whether there is evidence of such an effect. We do this by regressing the total investment inflow on measures of the overall shock to the compensation structure that advisors experienced in 2018.

Our first measure of the shock experienced by an advisor is the standard deviation (across the funds in the dataset) of the change in trailer fees in 2018. To understand why this measure captures the advisor's incentive to induce a rebalancing of investment, assume that there are only two funds. Further assume that the trailer fees of a certain advisor change, for both funds, from 1% to 2%. Because the fees in both funds have increased equally, the standard deviation of the change is zero. Intuitively, this zero value captures well the idea that the advisor has no new incentives to induce higher investment in a fund at the expense of the other.

Assume now instead that the trailer fees of the advisor increase by 1% in one fund and decrease by 1% in the other. The standard deviation of the change is now positive. This is consistent with the intuition that the advisor now has an incentive to allocate higher investments to the first fund and less to the second one. Given our earlier finding that the main mechanism for rebalancing involves getting the client to bring more money into the firm, we should find a positive relation between the standard deviation of the fee change and the inflow of total investment.

Our second measure of the shock experienced by an advisor is the average (across the funds in the dataset) change in trailer fees in 2018. As discussed with the previous example, a proportionate change across funds would not necessarily require the rebalancing of investment across funds. There are, however, two hypotheses linking an average increase in the trailer fees to additional client investment. On the one hand, standard incentive theory would posit that advisors receiving higher (average) trailer fees should be willing to devote more effort to increasing total client investment. On the other hand we find theories in which income effects are so strong that advisors choose to enjoy a 'quiet life'. For instance, advisors targeting a certain monthly income (Camerer et al., 1997) might exert less effort to increase client investment when the trailer fees are high enough that they can achieve their targeted compensation easily.

In Table 5 we construct a client/month panel dataset and regress total investment inflow on the two measures of shocks described above. We estimate the following DiD specification:

$$Investment_{ct} = \phi(Increase_{a(c)} \times Post_t) + \pi(SD_{a(c)} \times Post_t) + \beta_c + \kappa_t + \omega_{ct}, \quad (4)$$

Note further that the variations that we exploit in (1) and (4) are orthogonal to each other. In (1) we control for client/month indicators and therefore study to what funds clients allocate their investments *holding constant client's investment in that month*. The objective in (4) is to explain the client/month fixed effects, namely whether (aggregating across funds) clients bring money into their portfolio in a particular month. In this respect, the purpose of (4) is to explain the controls in (1).

In Figure 4 we plot the variation in our independent variables, $Increase_{a(c)}$ and $SD_{a(c)}$. As discussed in Section 2, a very large number of advisors (i.e. most post-2010 advisors) experienced no change in their compensation, and are therefore associated with values of zero for both shock measures. The pre-2010 advisors experienced a decrease in their fees, which typically was negative on average but different across different funds. Because the average and standard deviation of the change are negatively correlated with each other (t-statistic$=-17.52$), we present regressions in which we enter them, both separately and together. The amount of variation is relatively low, and the correlation between both variables is very strong ($r^2 = -.62$), so we expect our estimates to be quite noisy.

In Table 5, we find that advisors experiencing higher variability in the 2018 fee change persuade their clients to bring more investment into the firm. The effect is economically significant: a standard deviation increase (i.e. .071) increases the total net inflow by the advisor's clients by $7.7\% = .071 \times 1.086 \times 100$.[30] We also find that advisors with higher (average) fees induce lower investment inflows among their existing clients.

To conclude, we find support for the notion that advisors experiencing a heterogeneous change in their fees induce higher investment from their clients so that this new money can be allocated to their newly preferred funds. A decrease in the average fees is also associated with advisors encouraging higher investment from their clients, in order to compensate for the income lost from the lower fees. The effects are lower when both measures of the shock are included simultaneously, as one would expect given that the measures being negatively correlated with each other.[31]

[30]This finding prompts the question of why these advisors waited until the change in compensation policy to induce an increase in total investment, given that they would have benefited from such an increase prior to 2018. Inducing clients to increase their overall investment is likely to be associated with costs, in terms of persuasion effort, credibility depletion, etc. While a full-fledged persuasion model is outside the scope of this paper, one way to interpret the 2018 change in incentives is as increasing the wedge between the existing client allocation and the ideal allocation for the advisor under the new compensation. This wedge might in turn have increased the benefit of additional investment for the advisor, as additional investment is the easiest way to rebalance the client portfolio (Column 4 Table 3). In a cost-benefit framework, an increase in the marginal benefit would result in additional investment.

[31]Table A3 displays the coefficients using the outgoing and reallocation flows as dependent variables. Consistently with Columns 5 and 6 of Table 3, we find that our measures of the shock to incentives do not affect these total flows.

Effects on the Entry and Exit of Clients In Section 4, we have found that advisors find it easier to direct clients investments to their preferred funds when these clients are new to the firm, as opposed to clients who had joined prior to the 2018 change in compensation structure. An advisor experiencing a change in compensation might therefore have an incentive to devote more effort to finding new clients, even if that is at the expense of preventing existing clients from leaving the firm. In this subsection, we study whether there is evidence of such an effect. We do this by regressing the share of an advisor's clients that are new (or that have departed) on our measures of the shock to the compensation structure that advisors experienced in 2018.

We construct an advisor/month panel dataset and regress measures of client flows on the two measures of shocks to compensation from the previous subsection. We estimate the following DiD specification:

$$Clients_{at} = \phi(Increase_a \times Post_t) + \pi(SD_a \times Post_t) + \beta_a + \kappa_t + \omega_{at}, \tag{5}$$

We find in Columns 2-3 Table 6 that the number of new clients that an advisor has (as a share of total clients) is higher for advisors who experience a large shock to their compensation structure, as measured by the standard deviation of the fee change. On the other hand, we do not find in Columns 5-6 Table 6 that advisors with higher standard deviations of the fee change are associated with more clients departing. Columns 8-9 Table 6 put together these findings and show that client turnover (i.e. the sum of entries and exits) is positively associated with a higher shock to compensation. Together with the findings from the previous subsection, we interpret this evidence as suggesting that advisors that are hit strongly by a change to the compensation structure exert more effort to bring new money and clients to the firm, as these are the main channels through which advisors can direct investments to their newly preferred funds.[32]

[32]In Appendix Table A4 we use as dependent variables the total number of new and departing clients, as opposed to the share relative to the total number of clients. Because these new dependent variables typically take a small number of values (and often take value zero), we estimate Poisson regressions. We find broadly similar results, although there also seems to be an effect of the average increase in fee. In Appendix Table A5 we study whether the characteristics of clients are effected by the changes to the advisor's overall compensation structure. Broadly speaking, we do not find that advisors with higher average changes to compensation change the type of clients that they have. We also investigate that whether the time that clients spend with their advisors is affected by the changes to the advisor's overall compensation structure. We do not find in Appendix Table A6 that clients spend more or less time with advisors when these experience a higher shock to their overall compensation structure.

5 Effects on the Efficiency of Clients' Portfolios

In Section 3 we have shown that advisors' incentives affect clients' choices of individual funds. In this section we first examine whether the overall efficiency of clients' investment portfolio is affected by these incentives. We conclude the section by briefly discussing a framework to measure how incentives impact client utility.

Constructing Portfolios and Sharpe Ratios Our measure of portfolio efficiency is the Sharpe ratio. As we discuss below, this simple measure does not account for the (potentially suboptimal) match between portfolio characteristics and client risk preferences. Nevertheless it is uncontroversial that, holding this match constant, a high Sharpe ratio is a desirable property of an investment portfolio.

We undertake our exercise at the advisor level, grouping all clients of the same advisor together and computing portfolios and calculating Sharpe ratios for each of these groups.[33] In our first exercise, we focus on existing clients, which we define as those joining the firm before June 2017 and remaining with the firm after 2018.[34] We examine how their portfolios change between the periods before and after the incentive overhaul. To construct the portfolio for the post period, we use the average holdings for the six months after March 2018. To construct the portfolio for the pre period, we use average holdings for the six months after June 2017. We ignore the two months around the change in incentives because Figure 2 shows that existing clients adjust their incentives only gradually in response to the changes in their advisors' incentives. Computing the average portfolios during these two six-month periods, while disregarding the two months in between, allows us to account for this gradual change in portfolio composition.

Our second exercise examines the portfolios of new clients, before and after the change in incentives of their advisors. We define new clients in the post period as those joining the firm at any point in the six-month period starting in March 2018, and new clients in the pre period as those joining at any point in the six-month period starting in June 2017.

We construct two types of portfolios. Our first portfolio includes only internal funds, which are the focus of the main analysis in Sections 3 and 4, as there was no change in

[33] Undertaking this exercise at the advisor level reduces the effect of client idiosyncrasies on the estimation. It is however subject to the implicit assumption that clients of the same advisor hold portfolios with similar characteristics.

[34] We use June 2017 as the cutoff as we need a few months after the cutoff to construct the average portfolio.

advisor incentives for external products. Our second portfolio includes also other external products, such as external mutual funds, bonds, stock shares, etc. Studying this overall portfolio allows us to investigate whether any potential improvement in the Sharpe ratio of the internal fund portfolio is offset by worse investment performance of external products and/or if there is any correlation between internal and external portfolio returns. To calculate the Sharpe ratios of the portfolios in both the pre and the post periods, we use the average returns and variance-covariance matrix across products in the 48 months before June 2017.[35] By using these time-invariant average returns and covariances, we ensure that any potential improvement in Sharpe ratios is caused by changes across time in investment strategies, as opposed to changes in the return characteristics of different products.[36]

Effects on Sharpe Ratios and Exploration of Mechanisms Panel A Table 7 displays the Sharpe ratios for new clients. We find that the average annualised Sharpe ratio of the internal-fund portfolio increases from .712 in the pre period to .799 in the post period. This 12% increase is statistically significant at the 5% level. This indicates that new investors of the same advisors start to invest more efficiently following the 2018 change in incentives. In terms of the overall portfolio, which includes the external products, we find an increase from .499 to .601. The finding that the average Sharpe ratio improves also for the overall portfolio is important, as it indicates that clients are not using the external products to undo the changes in the internal funds portfolio.[37]

It is useful to distinguish three reasons for the documented improvement in Sharpe ratios following the 2018 change in incentives. First, the change in incentives may have caused advisors to steer their clients towards funds with different (before-fee) expected returns and risks. Second, advisors may have recommended funds with lower fees, holding constant (before-fee) returns and risks. Third, clients' investments may become more diversified and therefore may have generated lower risk at the portfolio level. The rationale

[35] Our results are robust to using different time periods (e.g., 24, 30, 36, 42 months before June 2017) to calculate the average returns and return covariances. Appendix Table A7 displays the results.

[36] By using returns only through June 2017 —before the weights of both pre- and post-policy portfolios are measured— we also mitigate any potential hindsight bias. If advisors had reallocated toward funds that earned high returns in this past window, any resulting inflation in Sharpe ratios would affect the pre-policy portfolios at least as much as the post-policy ones, making it unlikely that such bias accounts for the observed efficiency gains.

[37] It is interesting to note that the level of the Sharpe ratio is lower for the overall portfolio than that for the internal-fund portfolio. This is because external products include individual stocks which have higher idiosyncratic volatility and hence lower Sharpe ratios than diversified equity mutual funds.

behind the third mechanism is that advisors whose incentives do not strongly favour one fund over another are more likely to encourage their clients to invest in more funds, thus achieving higher portfolio diversification.

We do not explicitly investigate the first potential channel, as this would require measuring expected returns and risk accurately and this is difficult to achieve over short horizons. In Table 7 we provide evidence in support of the second and third channels. We find that the average percentage fee paid by investors on the internal funds decreases by .326% (from 1.741% to 1.416%) after the change in incentives, which represents a 19% decrease and is statistically significant at the 1% level. A large part of this decline in fees is due to clients' shifting some weights from equity funds to balanced funds and, to some extent, sector funds. To investigate the diversification channel, we compute the Herfindahl index of portfolio weights for the investments induced by each advisor. We find that the average Herfindahl index decreases from .504 to .429. This 15% decrease is statistically significant at the 10% level. Together, these two findings suggest that there are no perfect substitutes (with different fee levels) within each investment style. Instead, the existence of distorted incentives made advisors recommend suboptimal asset allocations (e.g., concentrating on a small number of equity funds), a situation that improved after 2018.

Table 7 displays changes across time in the portfolios of the new clients of the *average* advisor. However, we saw in Section 2 that some advisors were affected more by the changes in incentives. We might therefore expect more affected advisors to induce larger changes in the Sharpe ratios of their clients. To examine this relation we calculate the dispersion (i.e. standard deviation) in the trailer fees paid to an advisor, both before and after 2018.[38] The prediction is that the more homogeneous the trailer fees, the less distorted the portfolios recommended by advisors (in the extreme case where the trailer fees are identical across internal products, advisors have little incentive to recommend sub-optimal portfolios to their clients). We then regress the changes in Sharpe ratios on the changes in the advisor trailer fee dispersion. Figure 5 displays the results. We find a negative slope of -133, which is statistically significant at the 5% level. The size of the coefficient suggests that a one-standard-deviation increase in trailer fee dispersion generates a 0.078 increase in the Sharpe ratio of the portfolio.

[38] In the calculation of the standard deviation, we weigh each fund by their average pre-period (six months after June 2017) investment size. We find similar albeit noisier results using equal weights, which is likely caused by overstating the importance of relatively small funds.

In Panel B Table 7 we repeat the same exercise for the portfolios of existing investors. We do not find here any large or statistically significant changes between the pre period and the post period. The Sharpe ratio of the internal portfolio is for instance virtually identical between the two periods; the Sharpe ratio of the overall portfolio increases from .501 to .561, although the difference is statistically insignificant. The more muted response of existing investors is consistent with our earlier finding in Section 3 that the effects of the incentive overhaul on existing investors are smaller in magnitude than the effects on new investors.

Effects on Overall Utility In the previous subsection we have adopted a 'reduced form' approach to the study of the relation between advisor incentives and client utility. Using the Sharpe ratio as a measure of efficiency has the advantage that it imposes no modelling assumptions on investor preferences. However, it is precisely because client preferences are heterogeneous and unobserved that the mapping between the Sharpe ratio and client utility is not necessarily straightforward. In principle, a portfolio may deliver lower utility to a client than another portfolio with a lower risk-adjusted return, if this second portfolio is better suited to the idiosyncratic preference of that client. While the reduced form approach is transparent and intuitive, it ignores the potential inefficient matching between client preferences and the characteristics of their portfolios. This inefficient matching is not a second order concern, given that a core objective of investment advice is precisely to help clients find products matching their risk preferences.

In Appendix A we propose a simple framework to measure the change in client utility associated with the 2018 change in incentives. In our portfolio-choice model, investors have mean-variance preferences over portfolio returns, and their expectations about these returns are influenced by the incentives of their advisors. Based on these expectations, clients optimize over their mean-variance preferences. We estimate the parameters of the model and use these estimates to compute the average client utility loss, both prior to and following the 2018 change in compensation policy. We find that the misalignment of incentives was associated with large utility losses (around 9% for new clients and around 6% for existing clients) prior to the change in compensation policy. Most importantly, the January 2018 compensation policy decreased losses by more than a third for new clients and nearly one fifth for existing clients. Therefore, our analysis identifies substantial (albeit decreasing) utility losses associated with the misalignment of incentives.

6 External Validity and Concluding Remarks

We have provided evidence on the effects of advisors' incentives on the investments of their clients. In addition to showing well-identified economically large effects, the emphasis in our paper has been on the mechanisms through which advisors manage to induce changes in their clients' investments. We have found that clients are more likely to bring money into the firm (and direct this money into their advisors' preferred funds) when the incentives of their advisors change. Advisors also increase the number of new clients when affected by a change in incentives. We have found that the efficiency of the clients' portfolios (and clients' utility) improved significantly after the introduction of MiFID II, and we have explored the channels through which this increase in efficiency took place.

An important caveat of our analysis is that our empirical strategy is not designed to evaluate the overall consequences of MiFID II (even in our firm), given that MiFID II included several provisions regulating the financial advisory industry. More generally, note that the richness of our analysis has been made possible thanks to our focus on a single medium-sized investment firm, for which we have been able to gather uniquely precise data. While this granular focus has substantial advantages in terms of the identification of causal effects and the range of insights that we can generate, our 'insider econometrics' approach (Bandiera et al. 2011, Ichniowski and Shaw 2013) also poses the question of how our findings might extend to other settings and populations.

We have already discussed in Section 2 the characteristics of clients and advisors in our firm. To recap, the clients in our firm are broadly comparable to Spanish investors in mutual funds, although they seem to be devoting a larger than average proportion of their gross wealth to investing through our firm. Some of the firm advisors earn relatively little money and may be working part-time. This potentially limits the generalisability of our findings, with the caveat that the average firm client is advised by an advisor with high annual earnings. There is an additional aspect of our setting that might make the findings less generalisable. The advisors in our sample have self-selected to work as (broadly) exclusive dealers for a single mutual fund firm. To the extent that this indicates that they value their own compensation more than the utility of their clients, the findings in our paper may overestimate equivalent effects for other populations.

In terms of the setting, it differs from other important settings in some dimensions, while being similar in other dimensions. The fact that clients are charged a management fee, which is proportional to the amount invested is common both in the US (SEC,

2019) and in Europe (European Commission, 2018). Another feature of our setting is that advisors are compensated with a share of the firm's fee. Again, this is a pervasive compensation structure in many countries.[39] A third important feature of the advice relation in our setting is the lack of a fiduciary duty requirement. In the US, registered investment advisors are subject to this duty, but broker-dealers, which often offer similar services (Bhattacharya 2020), are not. Similarly to our setting, the lack of a fiduciary requirement is common in Canada (Linnainmaa et al., 2021) and in many Asian countries (Charoenwong and Kwan, 2019). Last, the advisor-client relation that we analyse is based upon the trust that generally lubricates financial relations (Sapienza and Zingales, 2011). Understanding the level of generalised trust in our context is important as this has been shown to determine how individuals interact with stock investments (Guiso et al., 2008). Spain has similar, perhaps slightly higher, levels of trust, compared to other developed economies (Ortiz-Ospina et al., 2024).[40] However our results are less likely to generalise to low-trust countries such as, for instance, those in Latin America.

The last caveat that we want to acknowledge is that our paper analyses the role of incentives within a fixed client-advisor relation, while being silent about the overall benefits that advisors may provide. We have already discussed that advisors can guide their clients towards higher diversification, increased savings and generally better investments (Lusardi and Mitchell 2011, 2014; Hastings et al. 2013, Gennaioli et al. 2015). Because of this, regulators have typically targeted advisor compensation while continuing to encourage access to financial advisors. We view the main value of our paper in terms of documenting the effects (and mechanisms through which these effects take place) of unbalanced compensation structures.

[39] In the US, O'Neal (1999) studies the twenty largest multiple-share-class equity funds and documents that a significant part of the annual fees charged to investors are paid to brokers in the form of a trailing fee. In the EU, EFAMA (2011) uses a representative sample of European mutual funds and reports that around half of the annual fees are paid back to distributors (see also European Commission, 2018). Although this percentage is likely to have decreased after MiFID II, recent survey evidence from Spain indicates that trailing fees remain important (Gimenez, 2018). On the other hand, trailing fees were banned in the UK by the 2013 Retail Distribution Review.

[40] The World Values Survey asks whether survey respondents agree with the statement that 'most people can be trusted'. 41% of 2022 Spanish respondents replied in the affirmative, as compared to 37% of US respondents. The percentages for the UK, Germany, Italy and France are 43%, 41%, 26% and 26% respectively.

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TABLE 1 - SUMMARY STATISTICS

Panel A: Clients (N= 6,132)	**Mean**	**SD**	**p10**	**p25**	**p50**	**p75**	**p90**	**Prop NonMiss**
Male	.66	.47	0	0	1	1	1	1
Year of Birth	1963	17	1942	1950	1963	1974	1986	.9
Financial Education Dummy	.19	.4	0	0	0	0	1	.5
Financial Profession Dummy	.09	.29	0	0	0	0	0	.51
Financial Knowledge Dummy	.35	.48	0	0	0	1	1	.48
High Income Dummy	.1	.31	0	0	0	0	1	.66
Year of Joining Firm	2007	30	1996	2000	2010	2014	2017	1
Total Investment in Firm	102,062	514,798	2,886	10,093	31,315	86,794	201,247	1
Gross Wealth	504,605	843,585	24,900	105,000	260,000	500,000	1,000,000	.51
Total Investment/Gross Wealth	.31	.3	.029	.078	.19	.42	.91	.51
Total Investment/Predicted Financial Wealth	.67	.35	.13	.33	.78	1	1	.51
Share Invested in External Products	.24	.29	0	0	.092	.46	.7	1

Panel B: EFF Fund Investors (N= 1,074)	**Mean**	**SD**	**p10**	**p25**	**p50**	**p75**	**p90**	**Prop. NonMiss**
Wealth	809,376	4,963,913	158,036	271,930	446,000	810,095	1,427,763	1
Investment in Funds	77,372	577,435	4,000	10,000	28,000	70,000	174,000	1
Investment in Funds/Gross Wealth	.11	.12	.011	.028	.068	.13	.27	1

Panel C: Advisors (N= 166)	**Mean**	**SD**	**p10**	**p25**	**p50**	**p75**	**p90**	**Prop. NonMiss**
Year of Contract	2007	8	1993	2000	2010	2013	2015	1
Post-2010 Dummy	.54	.5	0	0	1	1	1	1
Certified Dummy	.3	.46	0	0	0	1	1	1
Number of Clients	41	57	2	7	17	53	116	1
Annual Compensation	39,227	43,737	1,362	6,799	22,893	60,352	102,398	1

TABLE 1 - SUMMARY STATISTICS CONTINUED

Panel D: Client/Fund/Month (N= 3,637,984)	**Mean**	**SD**	**p10**	**p25**	**p50**	**p75**	**p90**	**Prop NonMiss**
Positive Investment Dummy	.19	.39	0	0	0	0	1	1
Investment	3,978	24,716	0	0	0	0	7,472	1
Share of Total Investment	.06	.19	0	0	0	0	.21	1
Net Investment Inflow	5	4,884	0	0	0	0	0	1
Trailer Fee	.97	.26	.63	.75	1	1.13	1.13	1

This Table displays summary statistics for the clients (Panel A), Spanish fund investors (Panel B), advisors (Panel C), and observations in the baseline client/fund/month dataset (Panel D). The last column displays the proportion of observations for which the variable is non-missing. The Financial Education Dummy is constructed on the basis of the questionnaire that clients have to fill as part of MiFID II. There are four possible answers: (a) '*No university education*', (b) '*University education that is not related to maths or economics*', (c) '*University education related to maths or economics*', (d) '*Education that is specific to financial markets and investment funds*'. The variable takes value one if the client answered (c) or (d). The Financial Profession Dummy captures whether the client '*works or has worked in a profession related to the financial markets*'. There are four possible answers: (a) '*I have never worked in a profession related to the financial markets*', (b) '*I have a job that, occassionally, is related to the financial markets*', (c) '*I have had a job that is related to the financial markets*', (d) '*I have a job that is related to the financial markets*'. The variable takes value one if the client answered (c) or (d). The Financial Knowledge Dummy is constructed on the basis of the question investigating whether the client is familiar with the '*nature, characteristics, and risks associated with investment funds*'. The question specifically asks about the '*degree of knowledge regarding the risks of the solicited products*'. There are four possible answers: (a) '*I do not understand any of the terms*', (b) '*I understand some of the terms and their descriptions*', (c) '*I understand all the terms and their general functioning*', (d) '*I understand all the terms and their functioning in detail*'. The variable takes value one if the client answered (c) or (d). The High Income Dummy is constructed on the basis of the questionnaire that clients have to fill as part of MiFID II. Clients are asked to report which bracket their income falls into: (a) '*0-20,000 Euros*', (b) '*20,000-60,000 Euros*', (c) '*60,000-100,000 Euros*', (d) '*More than 100,000 Euros*'. The variable takes value one if the client answered (c) or (d). Total Client Investment is the total investment by the client on an average month, including in the funds and products that are not in the baseline dataset. The Share of Investment in External Products is the share invested by the client in the firm in products that are not internal funds and includes all clients in the sample. The Gross Wealth is also based on the answers to MiFID II questionnaires. Total Investment in Funds in Panel B is the amount that the survey respondent invests in funds in all firms. Year of Contract is the year in which the advisor joined the firm. Post-2010 Dummy takes value one if the advisor joined the firm in 2010 or later. Certified Dummy takes value one if the advisor has acquired before December 2020 at least one of the approved financial advisor qualifications provided by the CISI (Chartered Institute for Securities and Investment) and EFPA (European Financial Planning Association). Number of clients is the total number of clients of the advisor over the 2015-2020 period. Annual compensation is the sum of the commissions received by the advisor, both from internal and from external funds. The Positive Investment Dummy takes value one if the client invested in the fund during that month. Investment is the amount invested in the fund in that month. Share of Total is the share of the total client's portfolio that is invested in the fund in that month. Net Inflow is the net value of all trades undertaken by the client on the fund in that month. Trailer Fee is computed as the fund's percentage fee (which is fixed both over time and across clients) multiplied by the commission, that is the percentage that the advisor receives (which varies within advisor/fund in January 2018).

TABLE 2: EXAMPLE OF VARIATION IN TRAILER FEES

Time			**Pre-2010**		**2010-2018 Change in Commissions for Post-2010 Advisors**		**Post-2018 Change in Commissions for Pre-2010 Advisors**	
		Fee %	**Commission**	**Trailer Fee**	**Commission**	**Trailer Fee**	**Commission**	**Trailer Fee**
Pre-2010	Fund A	1%	70%	.7%	70%	.7%	50%	.5%
Advisors	Fund B	2%	45%	.9%	45%	.9%	50%	1%
Post-2010	Fund A	1%			50%	.5%	50%	.5%
Advisors	Fund B	2%			50%	1%	50%	1%

This table illustrates the sources of variation in trailer fees. Advisors joining before 2010 were offered a contract with different commissions across funds. As an example, the table displays commissions of 70% and 45% for Funds A and B, respectively. Assuming respective percentage fees of 1% and 2%, this translates into trailer fees of .7% and .9%. Advisors joining after 2010 were offered a contract with the same commission across funds, such as the displayed 50%. This translates into trailer fees of .5% and 1% for Funds A and B. In 2018, the pre-2010 advisors were given the same contract as the post-2010 advisors.

TABLE 3
EFFECT OF TRAILER FEES ON INVESTMENT - EXISTING CLIENTS

	Investment Stocks			**Investment Flows**			
	(1) ihst Investment	**(2) Positive Investment**	**(3) Share of Total**	**(4) ihst Incoming**	**(5) ihst Outgoing**	**(6) ihst Reallocation**	**(7) ihst Net Inflow**
Log Trailer Fee	.463**	.041**	.022***	.115***	.022	-.01	.13***
	(.2)	(.02)	(.009)	(.036)	(.019)	(.008)	(.047)
Client/Fund F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Client/Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund/Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre-Trends Analysis - Dynamic Effects from Figures 2 and 3							
F-Statistic	.23	1.36	1.43	1.08	1.37	1.18	1
P-Value	.99	.2	.17	.38	.2	.31	.44

This Table displays estimates of regressions of clients' fund investments on the trailer fees that the clients' advisors receive when the clients invest in these funds. The estimating equation is:

$$Investment_{cjt} = \lambda LogTrailerFee_{a(c)jt} + \eta_{ct} + \kappa_{jt} + \mu_{cj} + \epsilon_{cjt},$$

The subscripts are a for advisor, c for client, j for fund and t for month. The unit of observation is a client/fund/month combination. Trailer Fee is computed as the fund's percentage fee (which is fixed both over time and across clients) multiplied by the commission, that is the percentage that the advisor receives (which varies within advisor/fund in January 2018). In (1) the dependent variable is the inverse hyperbolic sine transformation of the client investment in the fund in that month. In (2) the dependent variable is an indicator for whether the client invests a positive amount in the fund in that month. In (3) the dependent variable is the share of the total client's portfolio invested in the fund in that month. In (7) the dependent variable is the inverse hyperbolic sine transformation of the net value of all trades undertaken by the client on the fund in that month. In (4), (5) and (6) the dependent variables are the inverse hyperbolic sine transformations of the net value of all trades undertaken by the client on the fund in that month conditional on these trades occuring on days in which there were only incoming flows, outgoing flows or both types of trades, respectively. The bottom rows provide tests of the pre-trends assumptions in the dynamic effects regressions from Figures 2 and 3. We provide the F-statistic and P-value of the null hypothesis that $\pi_2 = \pi_3 = \ldots = \pi_{11} = 0$. Following Borusyak et al. (2024), we undertake these tests using only the observations prior to the shock whose effect we analyse. The estimating equation is:

$$Investment_{cfq} = \sum_{q=2\ldots11} \pi_q \Big(SHOCK_{a(c)f} \times Quarter_q \Big) + \eta_{cq} + \kappa_{fq} + \mu_{cf} + \epsilon_{cfq}$$

where $SHOCK_{a(c)f} = LogPost18TrailerFee_f - LogPre18TrailerFee_{a(c)f}$.
Standard errors are clustered at the advisor level. The number of observations in the regressions is 3,636,276. The number of clients is 6,132. The number of advisors is 166.

TABLE 4 - EFFECT OF TRAILER FEES ON THE INITIAL INVESTMENT OF NEW CLIENTS

	(1)	(2)	(3)
Dependent Variable:	**ihst Investment**	**Positive Investment**	**Share of Total**
Panel A: Without Client Characteristics X Fund Fixed Effects			
Log Trailer Fee	1.493***	.105***	.056***
	(.526)	(.04)	(.023)
Advisor/Fund Fixed Effects	Yes	Yes	Yes
Client Fixed Effects	Yes	Yes	Yes
Fund/Month Fixed Effects	Yes	Yes	Yes
Client Characteristics X Fund F.E.	No	No	No
Panel B: With Client Characteristics X Fund Fixed Effects			
Log Trailer Fee	1.472***	.103***	.057***
	(.507)	(.039)	(.023)
Advisor/Fund Fixed Effects	Yes	Yes	Yes
Client Fixed Effects	Yes	Yes	Yes
Fund/Month Fixed Effects	Yes	Yes	Yes
Client Characteristics X Fund F.E.	Yes	Yes	Yes

This table displays estimates of regressions of clients' fund investments (in the first quarter in which the clients join the firm) on the trailer fees that the clients' advisors receive when the clients invest in these funds. The estimating equation in Panel A is:

$$Investment_{cj} = \phi TrailerFee_{a(c)jt(c)} + \beta_c + \kappa_{jt(c)} + \iota_{a(c)j} + \omega_{cj},$$

The subscripts are a for advisor, c for client, j for fund and t for month. The unit of observation is a client/fund combination. The sample is restricted to include only clients joining the firm after January 2015. The sample further includes only the first quarter of these clients. Trailer Fee is computed as the fund's percentage fee (which is fixed both over time and across clients) multiplied by the commission, that is the percentage that the advisor receives (which varies within advisor/fund in January 2018). In Column (1) the dependent variable is the inverse hyperbolic sine transformation for the client investment in the fund in that quarter. In Column (2) the dependent variable is an indicator for whether the client invests a positive amount in the fund in that quarter. In Column (3) the dependent variable is the share of the total client's portfolio invested by the client in the fund in that quarter. The equation in Panel A includes advisor/fund, client and fund/quarter indicators. The equation in Panel B further includes interactions between the fund indicators and the following client characteristics: gender, age, a financial education dummy, a financial profession dummy, a financial knowledge dummy, and a high income dummy. The regression further includes interactions with indicators capturing whether the client characteristics above are missing. Standard errors are clustered at the advisor level. The number of observations in the regressions is 36,414. The number of clients is 2,730. The number of advisors is 144.

TABLE 5
EFFECT OF THE SHOCK TO THE ADVISOR'S OVERALL COMPENSATION ON THE TOTAL INFLOWS OF EXISTING CLIENTS

	ihst Total Net Inflow			ihst Total Incoming		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Average Fee Increase X Post	-.705***		-.391*	-.613***		-.355**
	(.25)		(.22)	(.185)		(.178)
S.D. Fee Change X Post		1.565***	1.086*		1.326***	.891**
		(.575)	(.613)		(.408)	(.451)
Client Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

This table displays estimates of regressions of clients' *total* investment inflows on characteristics of the changes in their advisors' trailer fees in January 2018. The first independent variable is the *average* (simple average over all the sample funds) increase in the trailer fee experienced by the advisor in January 2018. The second independent variable is the standard deviation (taken over all the sample funds) of the change in the trailer fee experienced by the advisor in January 2018. Both independent variables are interacted with the post January 2018 dummy. The estimating equation is in columns (3) and (6):

$$Investment_{ct} = \phi(Increase_{a(c)} \times Post_t) + \pi(SD_{a(c)} \times Post_t) + \beta_c + \kappa_t + \omega_{ct},$$

The subscripts are a for advisor, c for client and t for month. The unit of observation is a client/month combination. In Columns (1)-(3) the dependent variable is the inverse hyperbolic sine transformation of the net value of all trades undertaken by the client in that month, aggregated over all the funds. In Columns (4)-(6) the dependent variable is the inverse hyperbolic sine transformations of the net value of all trades undertaken by the client in that month conditional on these trades occuring on days in which there were only incoming flows. The regressions include client fixed effects and month fixed effects. Standard errors are clustered at the advisor level. N= 239,275; Clients=1,727; Advisors=164.

TABLE 6
EFFECT OF THE SHOCK TO THE ADVISOR'S OVERALL COMPENSATION ON THE ENTRY AND EXIT OF CLIENTS IN THE ADVISOR'S PORTFOLIO

	Incoming Clients (Share)			Departing Clients (Share)			Client Turnover (Share)		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Average Fee Increase X Post	-.019		-.005	-.001		.001	-.02*		-.003
	(.012)		(.01)	(.011)		(.012)	(.01)		(.01)
S.D. Fee Change X Post		.104***	.097***		.013	.015		.117***	.112***
		(.028)	(.031)		(.031)	(.034)		(.037)	(.04)
Advisor Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table displays estimates of regressions of advisors' portfolio of clients on characteristics of the changes in their trailer fees in January 2018. The first independent variable is the *average* (simple average over all the sample funds) increase in the trailer fee experienced by the advisor in January 2018. The second independent variable is the standard deviation (taken over all the sample funds) of the change in the trailer fee experienced by the advisor in January 2018. Both independent variables are interacted with the post January 2018 dummy. The estimating equation is in columns (3) and (6):

$$Clients_{at} = \phi(Increase_a \times Post_t) + \pi(SD_a \times Post_t) + \beta_a + \kappa_t + \omega_{at},$$

The subscripts are a for advisor and t for month. The unit of observation is a advisor/month combination. In Columns (1)-(3) the dependent variable is the number of new clients that the advisor obtained in month t, divided by the total number of clients. In Columns (4)-(6) the dependent variable is the number of clients that have left the advisor in month t, divided by the total number of clients. In Columns (7)-(9) the dependent variable is the sum of new clients and departing clients in month t, divide by the total number of clients. The regressions include advisor fixed effects and month fixed effects. Standard errors are clustered at the advisor level. N= 8,458; Advisors=166.

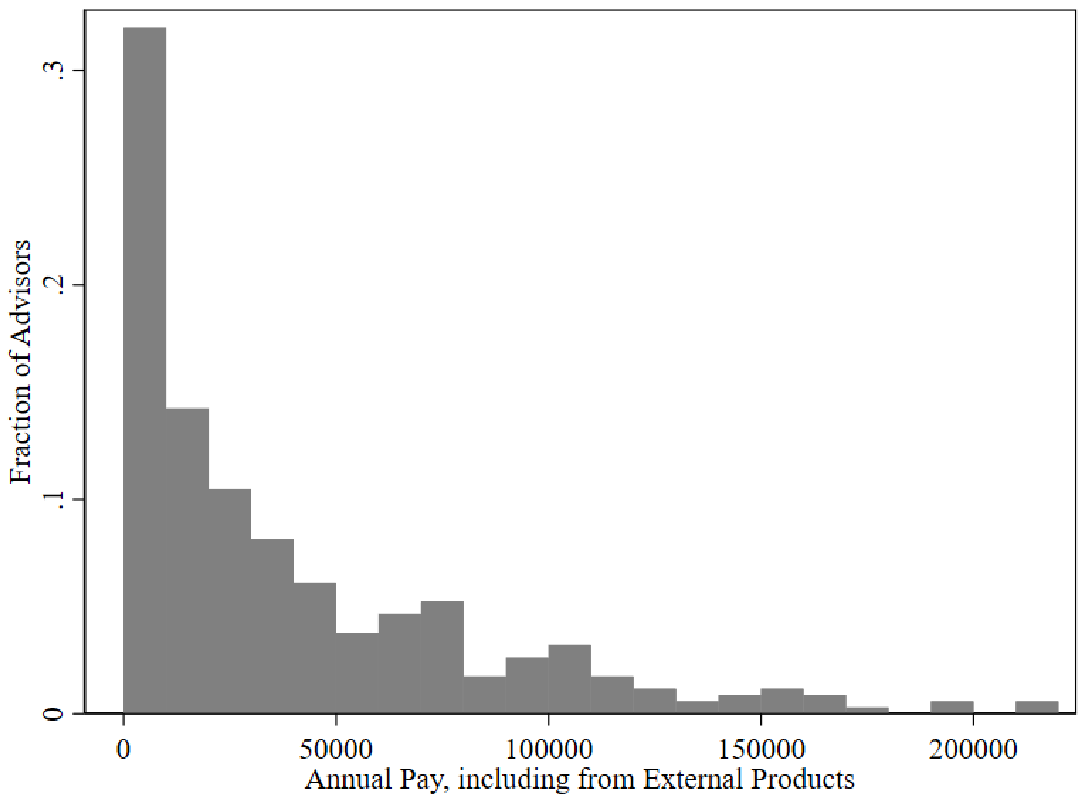
TABLE 7 – EFFECTS ON THE EFFICIENCY OF PORTFOLIOS

Panel A: New Clients	**Pre-2018**	**Post-2018**	**Change**	**t-statistic**
Sharpe Ratio (Internal Fund Portfolio)	.712	.799	.086	2.56
Sharpe Ratio (Overall Portfolio)	.499	.601	.102	1.99
Percentage Fee	1.741%	1.416%	-.326%	-3.78
Herfindahl Index	.504	.429	-.075	-1.82

Panel B: Existing Clients	**Pre-2018**	**Post-2018**	**Change**	**t-statistic**
Sharpe Ratio (Internal Fund Portfolio)	.684	.684	-.000	-.02
Sharpe Ratio (Overall Portfolio)	.501	.561	.060	1.54
Percentage Fee	1.648%	1.571%	-.077%	-1.67
Herfindahl Index	.264	.275	.011	.49

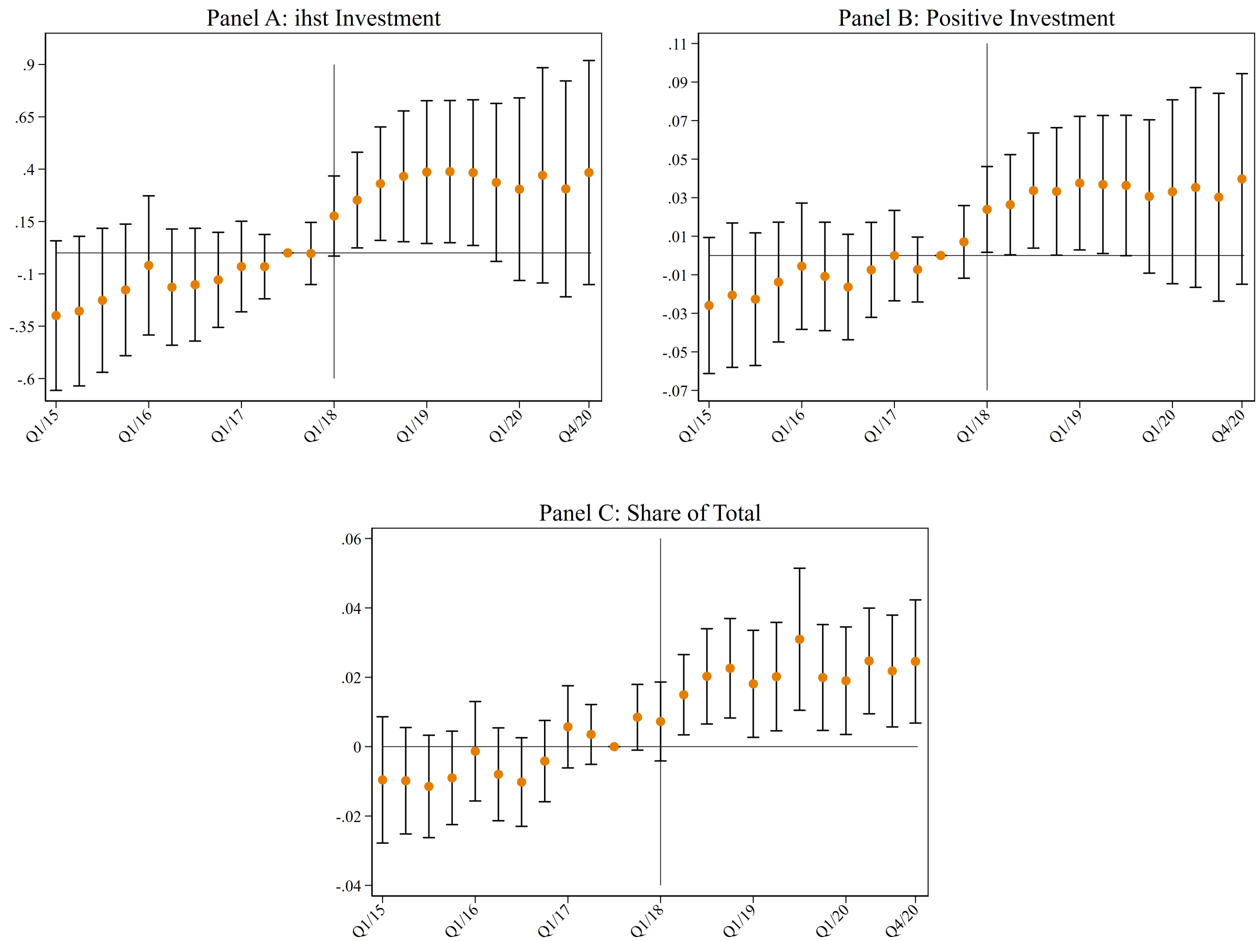
This Table displays Sharpe ratios for the portfolios of different groups of clients, both before and after the 2018 change in advisor incentives. Existing clients are defined as those joining the firm before June 2017 and remaining with the firm after 2018. New clients in the pre-2018 period are defined as those joining the firm in the six months after June 2017. New clients in the post-2018 period are defined as those joining the firm in the six months after March 2018. The portfolios of existing clients are computed using their average holdings in the six months after June 2017 (for the pre-period) and after March 2018 (for the post-period). The portfolios of new clients are computed using their average holdings in the three months after joining the firm. The Sharpe ratios are calculated using the same returns and variance-covariance matrix, regardless of the portfolio on which it is calculated. The returns and variance-covariance matrix are from the June 2013 to June 2017 period. Percentage fee is the fee being paid by clients to the firm, to compensate for the management of the investment in internal funds. Herfindahl index is based on the clients' investments on the internal funds. The portfolios are constructed at the advisor level, grouping all clients of the same advisor together.

FIGURE 1: DISTRIBUTION OF ADVISOR ANNUAL PAY



This figure displays the distribution of total annual pay for the advisors in the sample. The pay includes both the trailer fees received from the internal funds and the brokerage commissions received from the external products.

FIGURE 2: DYNAMIC EFFECTS ON THE STOCK OF INVESTMENT

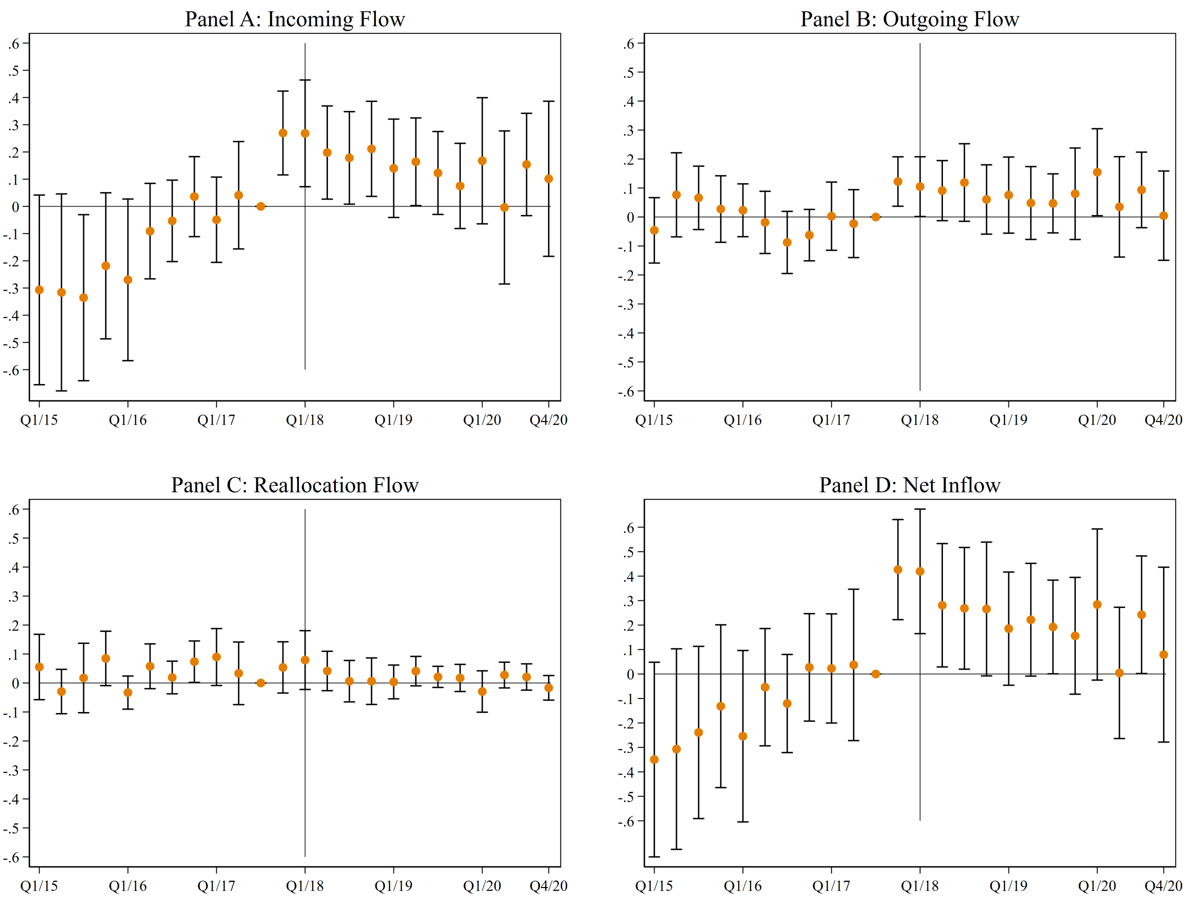


This figure displays the 24 coefficients π_q from estimating:

$$Investment_{cfq} = \sum_{q=1...10}^{12...24} \pi_q \Big(SHOCK_{a(c)f} \times Quarter_q \Big) + \eta_{cq} + \kappa_{fq} + \mu_{cf} + \epsilon_{cfq}$$

where $SHOCK_{a(c)f} = LogPost18TrailerFee_f - LogPre18TrailerFee_{a(c)f}$.
The unit of observation is a client/fund/quarter combination. The number of observations is 1,239,966. The number of clients is 6,132. The number of advisors is 166. The number of quarters is 24 (from Q1 2015 to Q4 2020). The variable for Q3 2017 is the omitted variable in the regression. The post-2018 trailer fee is computed as the fund's management fee (which is fixed both over time and across clients) multiplied by the share of the management fee that the advisor received after January 2018 (which is fixed across all advisors and funds). The pre-2018 trailer fee is computed as the fund's management fee multiplied by the share of the management fee that the advisor received prior to January 2018 (which varies both across advisors and across funds). In Panel A, investment is the inverse hyperbolic sine transformation of the client's average investment in the fund in the quarter. In Panel B, investment is a positive investment dummy. In Panel C, investment is the share of the total client investment in that quarter allocated to a specific fund. The regression controls for client/quarter, quarter/fund and client/fund indicators. Standard errors are clustered at the advisor level. 90% confidence intervals are displayed by capped vertical lines.

FIGURE 3: DYNAMIC EFFECTS ON THE FLOWS OF INVESTMENT

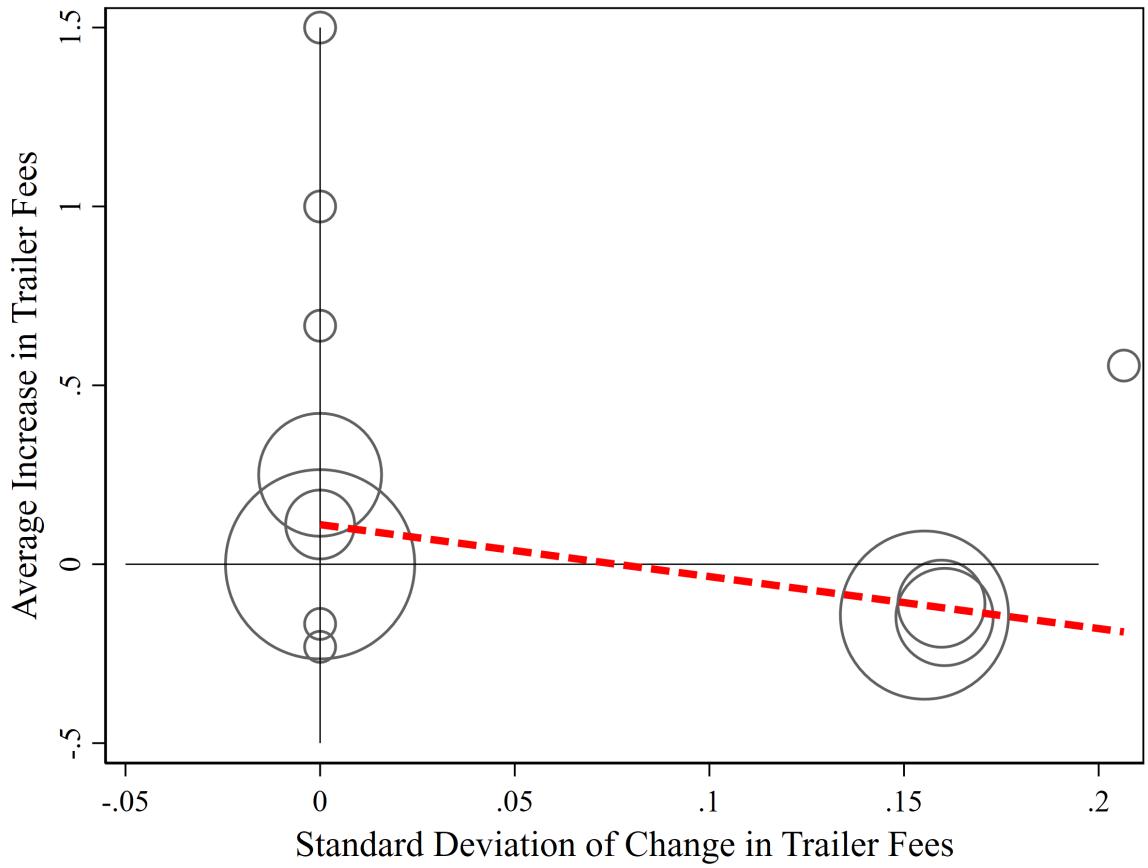


This figure displays the 24 coefficients π_q from estimating:

$$Investment_{cfq} = \sum_{q=1...10}^{12...24} \pi_q \Big(SHOCK_{a(c)f} \times Quarter_q \Big) + \eta_{cq} + \kappa_{fq} + \mu_{cf} + \epsilon_{cfq}$$

where $SHOCK_{a(c)f} = LogPost18TrailerFee_f - LogPre18TrailerFee_{a(c)f}$.
The unit of observation is a client/fund/quarter combination. The number of observations is 1,239,966. The number of clients is 6,132. The number of advisors is 166. The number of quarters is 24 (from Q1 2015 to Q4 2020). The variable for Q3 2017 is the omitted variable in the regression. The post-2018 trailer fee is computed as the fund's management fee (which is fixed both over time and across clients) multiplied by the share of the management fee that the advisor received after January 2018 (which is fixed across all advisors and funds). The pre-2018 trailer fee is computed as the fund's management fee multiplied by the share of the management fee that the advisor received prior to January 2018 (which varies both across advisors and across funds). In Panel D the dependent variable is the inverse hyperbolic sine transformation of the net value of all trades undertaken by the client on the fund in that month. In Panels A-C the dependent variables are the inverse hyperbolic sine transformations of the net value of all trades undertaken by the client on the fund in that month conditional on these trades occuring on days in which there were only incoming flows, outgoing flows or both types of trades, respectively. The regression controls for client/quarter, quarter/fund and client/fund indicators. Standard errors are clustered at the advisor level. 90% confidence intervals are displayed by capped vertical lines.

FIGURE 4: VARIATION IN THE SHOCK TO THE ADVISOR'S OVERALL COMPENSATION



This Figure displays the relation between two summary statistics of the change to the advisors' overall compensation. The first statistic is the average increase in the trailer fees. The second statistic is the standard deviation of the change in trailer fees. Both statistics are calculated over the total number of funds. The size of the circles reflect the number of advisors in each average/sd combination. The dashed line reflects the linear regression between both statistics.

FIGURE 5: RELATION BETWEEN CHANGE IN TRAILER FEES AND CHANGE IN SHARPE RATIOS

This figure displays the relation between the change in the standard deviation of the trailer fees of an advisor, and the change in the Sharpe ratios of the advisor clients' portfolios.

INTERNET APPENDIX

APPENDIX A: Measuring Client Utility Loss

In this section we propose a framework to estimate investors' utility loss. The starting point of our exercise is a simple portfolio-choice model in which investors have mean-variance preferences over portfolio returns, and in which their expectations about these returns are influenced by the incentives of their advisors. Specifically, we assume that advisors influence their clients' portfolio choice by strategically communicating the expected returns of the various internal funds. Based on this information, clients then optimize over their mean-variance preferences. We estimate the parameters of the model and use these estimates to compute the average client utility loss, both prior to and following the 2018 change in compensation policy.

Clients' Preferences We assume that clients' preferences, as defined over their portfolio returns, can be written as:

$$\mathbb{E}_c[U] = w_c'(\mathbb{E}_c[R] - R_f) + R_f - \frac{\gamma}{2} w_c' \Sigma w_c, \tag{1}$$

where R is a vector of asset returns, $\mathbb{E}_c[R]$ is a vector of client c's subjective expected asset returns, R_f is the return of the risk-free asset, Σ is the variance-covariance matrix of asset returns, and w_c is the vector of portfolio weights. The client's optimal portfolio is then given by:

$$w_c^* = (\gamma \Sigma)^{-1}(\mathbb{E}_c[R] - R_f). \tag{2}$$

We model expected utility such that clients are heterogeneous in their beliefs (i.e. $E_c[R]$) but homogeneous in their preferences, as reflected in the common risk aversion coefficient γ. This is without loss of generality because in a mean-variance framework, heterogeneity in preferences and heterogeneity in beliefs are isomorphic from a modelling perspective.[1] Note that we focus on the allocation of investments *across funds*. This is equivalent to assuming that advisors do not affect the overall level of investment.[2]

Advisors' Preferences Advisors are risk neutral on the income they generate from clients. They wish to maximise their short-term income, but also partially internalise client welfare.[3] Therefore, advisor a's preferences are defined as $U_a = \phi \mathbb{E}_c[U] + (1 - \phi) w_c' TF_{a(c)}$, where $\phi \in (0, 1)$ captures the concern for client welfare. For ease of interpretation, we write down the vector of trailer fees $TF_{a(c)}$ as being demeaned at the advisor level to reflect the fact that

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[1] In our setting, we can reinterpret the numerator in equation (2) as the subjective risk premium per unit of individual risk aversion, and this allows us to set γ to a constant for all clients.

[2] While this is consistent with the main empirical strategy in Sections 3 and 4, note that in Table 4 we find that the change in compensation policy was associated with an increase in overall investment. If this increase generated additional distortions, we can interpret the client utility effects estimated in this section as an underestimate of the true utility effects.

[3] Partially internalising client welfare can be interpreted as the reduced form of a model in which the advisor can acquire a good reputation and takes into account the stream of trailer fees over an infinite horizon (Mailath and Samuelson, 2001).

advisors' incentives are determined by the *relative* trailer fees they receive from the funds. U_a can be rewritten as:

$$U_a = \phi(w_c^{'}(\mathbb{E}_c[R] - R_f) + R_f - \frac{\gamma}{2}w_c^{'}\Sigma w_c) + (1-\phi)w_c^{'}TF_{a(c)}, \tag{3}$$

The advisor's desired investment by their client can be written as:

$$w_a^* = (\gamma\Sigma)^{-1}\left(\mathbb{E}_c[R] - R_f + \alpha TF_{a(c)}\right) = w_c^* + \frac{\alpha}{\gamma}\Sigma^{-1}TF_{a(c)}. \tag{4}$$

where $\alpha = \frac{1-\phi}{\phi}$ is the *bias* in the preferences of the advisor, relative to those of the client.

Information Transmission Given our set of assumptions, (4) shows that the (demeaned) trailer fees of advisors linearly affect their *preferred* clients' investments. Given this linear bias in the preferred decision, we can motivate a linear relation between the incentives of advisors and the *actual* clients' investments with a simple strategic information transmission game à la Kartik et al. (2007).

Assume that the advisor sends a set of messages about the expected return of each fund and, on the basis of these messages, the (potentially naïve) client forms (potentially distorted) beliefs $\hat{\mathbb{E}}_c[R]$. Kartik et al. (2007) show that, in equilibrium, the advisor can induce client beliefs to be equal to $\hat{\mathbb{E}}_c[R] = \mathbb{E}_c[R] + \alpha TF_{a(c)}$, where α (i.e. the 'bias') can be reinterpreted as the sensitivity of the client beliefs to the advisor's incentives.[4] In turn, these beliefs can induce the client to choose their actual investment $\hat{w}_c^*$ as follows:

$$\begin{aligned} \hat{w}_c^* = arg\max_{\hat{w}_c}\hat{\mathbb{E}}_c[U] &= arg\max_{\hat{w}_c}\hat{w}_c^{'}(\hat{\mathbb{E}}_c[R] - R_f) + R_f - \frac{\gamma}{2}\hat{w}_c^{'}\Sigma\hat{w}_c \\ &\Rightarrow \hat{w}_c^* = (\gamma\Sigma)^{-1}(\hat{\mathbb{E}}_c[R] - R_f) \end{aligned} \tag{5}$$

where $\hat{\mathbb{E}}_c[U]$ are the client's expected utility given distorted beliefs. Note that (5) makes the actual investment chosen by the client (i.e. $\hat{w}_c^*$) to be equal to the preferred investment by the advisor (i.e. w_a^*).

Estimating the Parameters of the Model We use the framework above to conceptualise and quantify client utility loss. To do this, we need to estimate the unknown parameters of the model, starting with the (common) risk aversion coefficient γ. We can infer clients' risk aversion from the properties of their portfolios under the distorted beliefs. Multiplying both sides of (5) by $\gamma\hat{w}_c^{*'}\Sigma$ we have:

$$\gamma\sigma_c^{*2} = \hat{\mathbb{E}}_c[R]^* - R_f, \tag{6}$$

where $\hat{\mathbb{E}}_c[R]^*$ and σ_c^{*2} are the (distorted) expected return and variance of the client's optimal portfolio. In reality, optimal portfolio weights are subject to a set of unobservable, individual-specific constraints and frictions. To mitigate the impact of such idiosyncratic noise, we

[4]An intuitive feature of this expression is that advisor-induced distortions in expected beliefs about a fund are only relative to other funds, and wash out in aggregate (remember that $TF_{a(c)}$ is a vector of mean zero).

aggregate all individual clients into a representative client (on an investment-value-weighted basis), and rewrite equation (6) for this representative investor as:

$$\gamma = (\hat{\mathbb{E}}[R_m]^* - R_f)\sigma_m^{*-2}, \tag{7}$$

where $\hat{\mathbb{E}}[R_m]^*$ and σ_m^{*2} are the (distorted) expected return and variance of the aggregate 'market' portfolio.[5] We further assume that, in the absence of advisor influence, clients hold a common belief about the expected market return (which, for example, can be inferred from historical returns). We then estimate γ, together with the bias parameter α, using a recursive fixed-point method which we describe in more detail below. In Table 8, we use (7) to compute the value of γ given the observed moments of the aggregate portfolio and a set of reasonable assumptions on the risk-free rate R_f.

The second parameter we need to estimate is the effect of advisor incentives on client beliefs, α. We exploit the fact that the compensation policy in January 2018 changed advisors' trailer fees and, through them, the distortion in the beliefs of their clients. We rewrite (5) for both the pre and post January 2018 periods.

$$\begin{aligned} \hat{w}_c^{*pre} &= (\gamma\Sigma)^{-1}(\hat{\mathbb{E}}_c^{pre}[R] - R_f) \\ \hat{w}_c^{*post} &= (\gamma\Sigma)^{-1}(\hat{\mathbb{E}}_c^{post}[R] - R_f). \end{aligned}$$

Taking the difference and assuming that $\mathbb{E}_c[R]$ does not vary over time, we have:

$$\Delta\hat{w}_c^* = \hat{w}_c^{*post} - \hat{w}_c^{*pre} = (\gamma\Sigma)^{-1}\alpha\Delta TF_{a(c)}. \tag{8}$$

where $\Delta TF_{a(c)}$ is a vector of changes in the (demeaned) trailer fees. Given γ and Σ, we can then estimate α in a linear equation.

Lastly, quantifying clients' utility loss requires calculating their subjective expected returns in the absence of the advisor-induced distortion in beliefs. Note that these can be easily computed by rewriting equation (5) as:

$$\mathbb{E}_c[R] = \gamma\Sigma\hat{w}_c^* - \alpha TF_{a(c)} + R_f.$$

After calculating $\mathbb{E}_c[R]$ for every client we can compute the optimal portfolio weights w_c^*, in the absence of distorted beliefs, as:

$$w_c^* = (\gamma\Sigma)^{-1}(\mathbb{E}_c[R] - R_f).$$

Quantifying Utility Loss We use equation (1) to compute the difference between the realised client utility (which depends on $\hat{w}_c^*$) and the utility that clients would have obtained in the absence of distortions (which depends on w_c^*).

$$Loss_c = (w_c^* - \hat{w}_c^*)'(\mathbb{E}_c[R] - R_f) - \frac{\gamma}{2}(w_c^{*\prime}\Sigma w_c^* - \hat{w}_c^{*\prime}\Sigma\hat{w}_c^*).$$

Note that $\hat{w}_c^*$ is observed, and w_c^* and $Loss_c$ can be computed, separately for the periods before and after January 2018. We can then calculate $\Delta U_c = Loss_c^{pre} - Loss_c^{post}$ to quantify the improvement in client utility resulting from the 2018 change in compensation policy.

[5] Note that advisor influence washes out if we take an equal-weighted average across all internal funds. This relation, however, does not hold exactly when we take an investment-value-weighted average across internal funds, as the investment value in each fund is partially determined by advisor influence.

Discussion of Assumptions Before discussing the data and results, it is important to emphasise that our stylised model abstracts from a number of considerations that may be affecting advice and investment decisions in practice. Firstly, we assume that the only biases caused by advisors are due to misalignments of incentives and not, for instance, to their own biased beliefs (Foerster et al. 2017, Linnainmaa et al. 2021). Secondly, we implicitly assume that there are no time costs associated with studying, evaluating, and communicating the likely returns of different funds. In practice, however, these costs may be substantial and differ across funds, which might create a rationale for fund-specific advisor compensation. Lastly and also unrealistically, the clients in our model lack access to both additional funds and additional sources of information.

A comprehensive model of investment advice remains outside the scope of this paper (Inderst and Ottaviani, 2012a). Instead, our objective is to show that, under admittedly strong assumptions, our empirical estimates can be used to provide guidance about the likely costs of the distortions induced by incentive misalignment.[6]

Data and Results As shown earlier, the 2018 compensation policy had a larger impact on the portfolio choice of new clients than that of existing clients. A natural interpretation of this difference is that, without clients' inertia in their investment choices and advisors' unwillingness to contradict their earlier advice, the estimated effect for existing clients would have been comparable to that of new clients. Under this assumption, we estimate our main parameter α focusing solely on the set of new clients, and then apply the same α to existing clients.

To compute the risk-aversion coefficient γ, we assume that the representative investor uses historical returns (i.e. before June 2017) to form their opinions about the market expected return and variance in the absence of advisor influence. Note that $\hat{\mathbb{E}}[R_m]^*$ in equation (7) is the expected market return with distortion, which depends on the value of α. We therefore take a recursive approach to estimating γ and α. Specifically, we start with an α of zero to estimate the value of γ using equation (7). We then plug in the estimate of γ to equation (8) to derive a new estimate for α. We keep iterating this two-step procedure until arriving at a fixed-point solution for both γ and α.

Finally, while the optimal portfolio choice in (5) is an interior solution, in practice we observe that most clients invest in a small number of internal funds.[7] To approximate the empirical framework to the assumptions of the model, we aggregate clients with the same advisor to a client group (by summing up their investment in each fund), and estimate the expected utility loss at the advisor level. We further aggregate investments in all external products into three groups: the first group includes all external (equity and balanced) mutual funds, the second one includes all stocks, and the third all fixed-income products (mostly in money market funds, so closely tracking the risk free rate).[8]

[6] One last caveat in our exercise is that the reduced form estimates and the corresponding estimated utility losses may not generalise to different populations. We discuss the similarities and differences between the clients and advisors in our sample and those in other settings in Section 8.

[7] This can be consistent with investors facing a fixed cost to invest in an additional mutual fund.

[8] Some investors in our sample also hold derivative and structure products. These are not included in our estimation, as a) we do not have good pricing data for these products and b) they account for a relatively small portion of investor wealth.

Appendix Table A8 displays the full results from the model estimation, with risk-free rates ranging from 0 to 5%. We report utility losses separately for new clients and existing clients (as defined in Section 5). We draw several conclusions from the table. Firstly, our estimates for the risk aversion coefficient, between 1.23 and 0.76, are largely in line with estimates from prior work.[9] Secondly, we find substantial utility losses (around 9% for new clients and 6% for existing clients) prior to the change in compensation policy.[10] Last and perhaps most importantly, the January 2018 compensation policy decreased losses by roughly 40% for new clients and 20% for existing clients. Overall, our analysis identifies substantial utility losses associated with the misallocation of investments caused by the misalignment of incentives.

References for Appendix A

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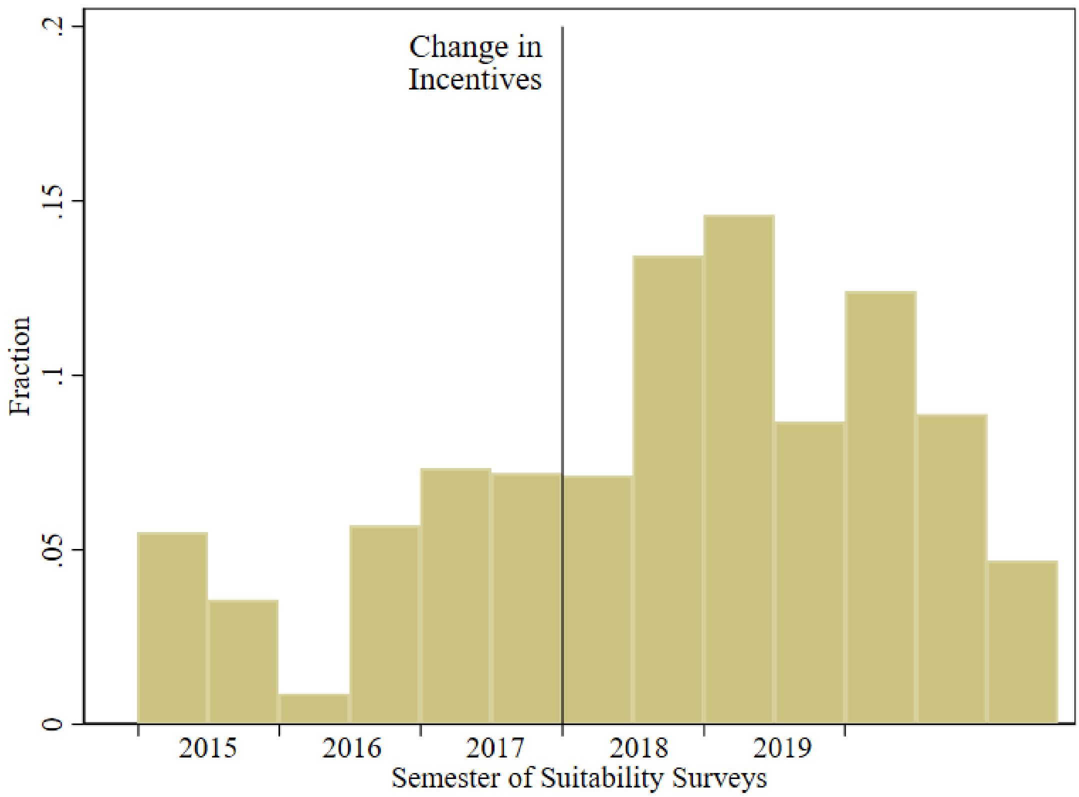
[9] See, for example, Friend and Blume (1975), Kydland and Prescott (1982), and more recently Calvet, Campbell, Gomes, and Sodini (2021).

[10] The difference in estimated utility loss between new and existing clients is likely due to noise in the data, especially given the relatively small number of new clients in the estimation procedure.

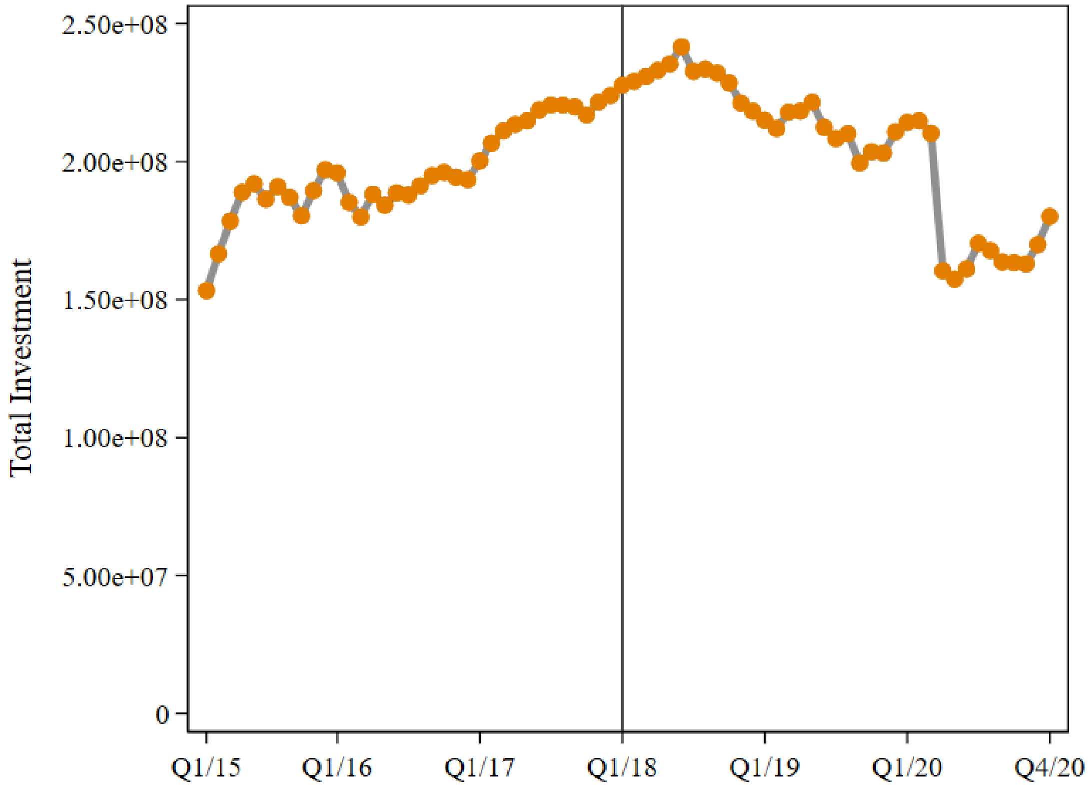
APPENDIX B: FIGURES AND TABLES

FIGURE A1: TIMING OF SUITABILITY SURVEYS COMPLETED BY THE FIRM CLIENTS



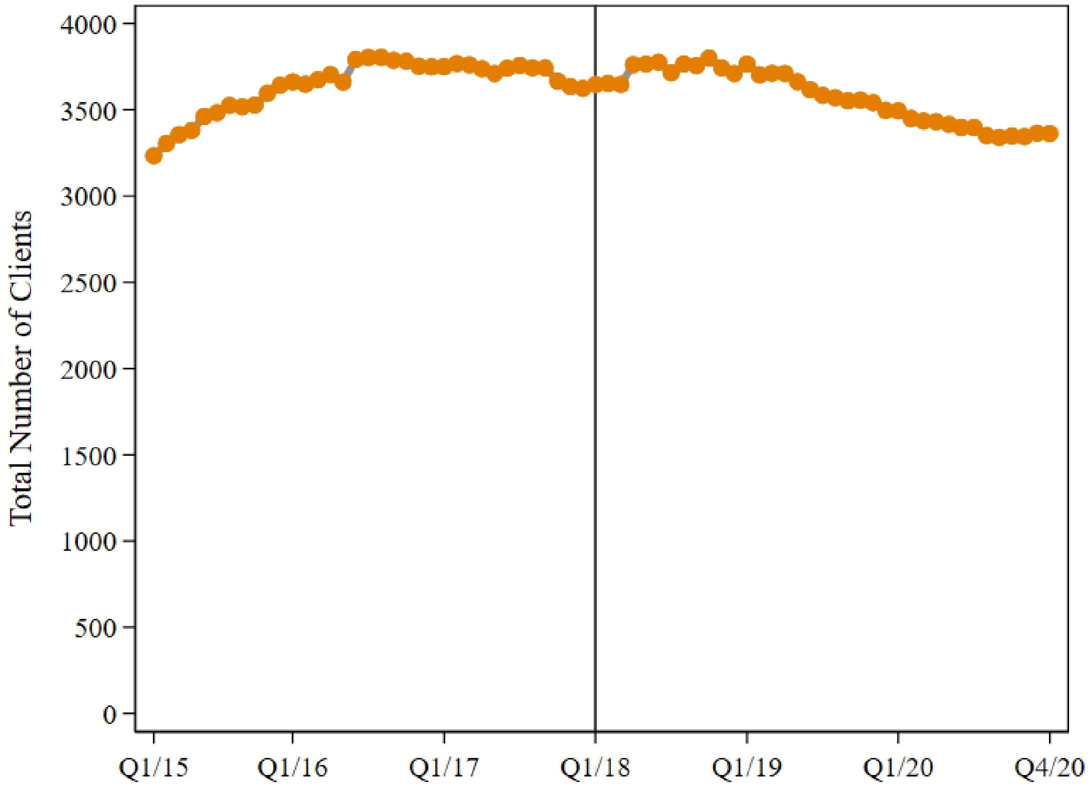
This histogram displays the timing of the suitability surveys introduced by the firm and prompted by the approval of MiFID II in April 2014. The vertical black line denotes the January 2018 change to incentives in the firm.

FIGURE A2: TOTAL INVESTMENT BY THE FIRM'S CLIENTS



This figure displays the total investment amount by the firm's clients.

FIGURE A3: TOTAL NUMBER OF CLIENTS



This figure displays the total number of clients.

TABLE A1 - ROBUSTNESS TO DIFFERENT FUNCTIONAL FORMS
EFFECT OF TRAILER FEES ON INVESTMENT (EXISTING CLIENTS)

Dependent Variable:	(1) ihst Investment	(2) Log Investment+1	(3) Poisson Model	(4) Investment	(5) Investment
Log Trailer Fee	.463**	.434**	1.824***	2902.863***	
	(.2)	(.187)	(.289)	(1242.996)	
Trailer Fee					2606.764***
					(1039.242)
Client/Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes
Client/Month Fixed Effects	Yes	Yes	Yes	Yes	Yes
Fund/Month Fixed Effects	Yes	Yes	Yes	Yes	Yes

This Table displays estimates of regressions of clients' fund investments on the trailer fees that the clients' advisors receive when the clients invest in these funds. The estimating equation is:

$$Investment_{cjt} = \lambda LogTrailerFee_{a(c)jt} + \eta_{ct} + \kappa_{jt} + \mu_{cj} + \epsilon_{cjt},$$

Trailer Fee is computed as the fund's percentage fee (which is fixed both over time and across clients) multiplied by the commission, that is the percentage that the advisor receives (which varies within advisor/fund in January 2018). The unit of observation is a client/fund/month combination. In (1) the dependent variable is the inverse hyperbolic sine transformation of the client investment in the fund in that month. In (2) the dependent variable is the log of investment plus one. In (3) we estimate a conditional quasi-maximum likelihood fixed-effect Poisson model. We display the incidence rate ratio (i.e. the exponential of the coefficient). In (4)-(5) the dependent variable is the investment level. In (5) the independent variable is the trailer fee. Standard errors are clustered at the advisor level. The number of observations in the regressions is 3,636,276. The number of clients is 6,132. The number of advisors is 166.

TABLE A2 - ROBUSTNESS TO KEEPING ONLY ADVISORS WITH RELATIVELY HIGH AVERAGE ANNUAL PAY

Restriction:	**(1) None (Baseline)**	**(2) Above 2017 Minimum Wage**	**(3) Above 30th Percentile**	**(4) Above 50th Percentile**	**(5) Above 70th Percentile**
Log Trailer Fee	.463**	.497**	.454**	.567***	.433*
	(.2)	(.218)	(.207)	(.221)	(.262)
Client/Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes
Client/Month Fixed Effects	Yes	Yes	Yes	Yes	Yes
Fund/Month Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	3,636,276	3,344,530	3,505,320	3,227,196	2,535,190
Number of Clients	6,134	5,548	5,862	5,282	4,056
Number of Advisors	166	99	116	83	49

This Table displays estimates of regressions of clients' fund investments on the trailer fees that the clients' advisors receive when the clients invest in these funds. The estimating equation is:

$$Investment_{cjt} = \lambda LogTrailerFee_{a(c)jt} + \eta_{ct} + \kappa_{jt} + \mu_{cj} + \epsilon_{cjt},$$

The dependent variable is the inverse hyperbolic sine transformation of the client investment in the fund in that month. The trailer fee is computed as the fund's management fee (which is fixed both over time and across advisors/clients) multiplied by the share of the management fee that the advisor receives (which varies, within advisor/fund, in January 2018). The unit of observation is a client/fund/month combination. In (1) there are no restrictions to the sample. In (2) we restrict the sample to include only advisors that on average make more than the 2017 minimum wage. In (3) we restrict the sample to include only advisors whose average annual pay is above the 30th percentile. In (4) we restrict the sample to include only advisors whose average annual pay is above the 50th percentile. In (5) we restrict the sample to include only advisors whose average annual pay is above the 70th percentile. Standard errors are clustered at the advisor level.

TABLE A3
EFFECT OF THE SHOCK TO THE ADVISOR'S OVERALL COMPENSATION ON THE TOTAL FLOWS OF EXISTING CLIENTS

	ihst Total Outgoing			ihst Total Reallocation		
	(1)	(2)	(3)	(4)	(5)	(6)
Average Fee Increase X Post	-.044		.002	-.033		-.031
	(.094)		(.089)	(.024)		(.021)
S.D. Fee Change X Post		.158	.16		.044	.006
		(.296)	(.336)		(.059)	(.059)
Client Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

This table displays estimates of regressions of clients' *total* investment flows on characteristics of the changes in their advisors' trailer fees in January 2018. The first independent variable is the *average* (simple average over all the sample funds) increase in the trailer fee experienced by the advisor in January 2018. The second independent variable is the standard deviation (taken over all the sample funds) of the change in the trailer fee experienced by the advisor in January 2018. Both independent variables are interacted with the post January 2018 dummy. The estimating equation is in columns (3) and (6):

$$Investment_{ct} = \phi(Increase_{a(c)} \times Post_t) + \pi(SD_{a(c)} \times Post_t) + \beta_c + \kappa_t + \omega_{ct},$$

The subscripts are a for advisor, c for client and t for month. The unit of observation is a client/month combination. In Columns (1)-(3) the dependent variable is the inverse hyperbolic sine transformation of the net value of all trades undertaken by the client in that month conditional on these trades occuring on days in which there were only outgoing flows, aggregated over all the funds. In Columns (4)-(6) the dependent variable is the inverse hyperbolic sine transformations of the net value of all trades undertaken by the client in that month conditional on these trades occuring on days in which there were both incoming flows and outgoing flows, aggregated over all the funds. The regressions include client fixed effects and month fixed effects. Standard errors are clustered at the advisor level. N= 239,275; Clients=1,727; Advisors=164.

TABLE A4
EFFECT OF THE SHOCK TO THE ADVISOR'S OVERALL COMPENSATION ON THE ENTRY AND EXIT OF CLIENTS IN THE ADVISOR'S PORTFOLIO POISSON REGRESSIONS

	Number of Incoming Clients			Number of the Departing Clients		
	(1)	(2)	(3)	(4)	(5)	(6)
Average Fee Increase X Post	-1.227***		-.628	.323		.995
	(.478)		(.513)	(.8)		(.804)
S.D. Fee Change X Post		2.711**	1.908		1.273	2.608
		(1.186)	(1.401)		(1.998)	(2.314)
Client Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

This table displays estimates of regressions of the number of incoming and departing clients of an advisor on characteristics of the changes in their trailer fees in January 2018. The first independent variable is the *average* (simple average over all the sample funds) increase in the trailer fee experienced by the advisor in January 2018. The second independent variable is the standard deviation (taken over all the sample funds) of the change in the trailer fee experienced by the advisor in January 2018. Both independent variables are interacted with the post January 2018 dummy. The estimating equation is in columns (3) and (6):

$$Clients_{at} = \phi(Increase_a \times Post_t) + \pi(SD_a \times Post_t) + \beta_a + \kappa_t + \omega_{at},$$

The subscripts are a for advisor, c for client and t for month. The unit of observation is a advisor/month combination. In Columns (1)-(3) the dependent variable is the number of new clients that the advisor obtained in month t. In Columns (4)-(6) the dependent variable is the number of clients that have left the advisor in month t. The regressions include advisor fixed effects and month fixed effects. Standard errors are clustered at the advisor level. N= 7,803; Advisors=166.

TABLE A5
EFFECT OF THE SHOCK TO THE ADVISOR'S OVERALL COMPENSATION ON THE CHARACTERISTICS OF CLIENTS

	(1) Log Age	(2) Male Dummy	(3) Financial Knowledge Dummy	(4) Financial Education Dummy	(5) Financial Profession Dummy	(6) High Income Dummy	(7) Log Distance to Firm	(8) Log Distance to advisor
Average Fee Increase X Post	.008	.014	.247	-.006	-.014	-.044*	.009	.196
	(2.285)	(.033)	(.168)	(.027)	(.038)	(.024)	(.083)	(.143)
S.D. Fee Change X Post	1.992	.219	.5*	.03	-.064	-.055	-.057	1.192
	(4.574)	(.147)	(.266)	(.16)	(.217)	(.077)	(.575)	(.769)
Advisor Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table displays estimates of regressions of the characteristics of advisors' clients on characteristics of the changes in their trailer fees in January 2018. The first independent variable is the *average* (simple average over all the sample funds) increase in the trailer fee experienced by the advisor in January 2018. The second independent variable is the standard deviation (taken over all the sample funds) of the change in the trailer fee experienced by the advisor in January 2018. Both independent variables are interacted with the post January 2018 dummy. The estimating equation is:

$$AverageCharac_{at} = \phi(Increase_a \times Post_t) + \pi(SD_a \times Post_t) + \beta_a + \kappa_t + \omega_{at},$$

The subscripts are a for advisor and t for month. The unit of observation is a advisor/month combination. The regressions include advisor fixed effects and month fixed effects. The dependent variables capture the average characterisitic of the advisor clients, such as age, gender, financial knowledge, etc. Standard errors are clustered at the advisor level. N= 8,313; Advisors=166.

TABLE A6 - EFFECT OF THE SHOCK TO THE ADVISOR'S OVERALL COMPENSATION ON THE DURATION OF THE CLIENT-ADVISOR RELATION

Dependent Variable:	**(1) Change Advisor**	**(2) Log Duration with Advisor**	**(3) Log Duration with Advisor**
Average Fee Increase X Post	.006		
	(.007)		
S.D. Fee Change X Post	-.023		
	(.017)		
Average Fee Increase		.078	.08
		(.313)	(.314)
S.D. Fee Change		.506	.477
		(.843)	(.846)
Duration Before Jan 2018			.001
			(.002)
Client Fixed Effects	Yes	No	No
Month Fixed Effects	Yes	No	No
Observations	244,260	3,671	3,671

This table investigates whether the time that the client spends with an advisor is affected by shocks to the overall compensation of the advisor. The first independent variable is the *average* (simple average over all the sample funds) increase in the trailer fee experienced by the advisor in January 2018. The second independent variable is the standard deviation (taken over all the sample funds) of the change in the trailer fee experienced by the advisor in January 2018. The estimating equation in Column 1 is:

$$ChangeAdvisor_{ct} = \phi(Increase_{a(c)} \times Post_t) + \pi(SD_{a(c)} \times Post_t) + \beta_c + \kappa_t + \omega_{ct},$$

The subscripts are a for advisor, c for client and t for month. The unit of observation is a client/month combination. The dependent variable $ChangeAdvisor$ is a dummy taking value one if the client changed advisor between the current month and the previous one. Both independent variables are interacted with the post January 2018 dummy. The regressions include client fixed effects and month fixed effects. The estimating equation in Columns 2 and 3 is:

$$LogDuration_c = \phi Increase_{a(c)} + \pi SD_{a(c)} + \omega_c,$$

where $LogDuration$ is the log of the duration in months that the client spent with their current advisor after January 2018. In other words, $LogDuration$ starts counting in January 2018, regardless of how long the client has spent with the advisor prior to that. The unit of observation is a client. In Column 3 we control for the time that the client has been with the advisor prior to January 2018. Standard errors in all models are clustered at the advisor level.

TABLE A7 - EFFECTS ON THE EFFICIENCY OF PORTFOLIOS ROBUSTNESS TO USING DIFFERENT HORIZONS FOR THE CALCULATION OF EXPECTED RETURNS AND COVARIANCES

Panel A: 48 Months (Baseline)	**Pre-2018**	**Post-2018**	**Change**	**t-statistic**
Sharpe Ratio (New Clients)	.712	.799	.086	2.56
Sharpe Ratio (Existing Clients)	.684	.684	-.000	-.02
Panel B: 42 Months	**Pre-2018**	**Post-2018**	**Change**	**t-statistic**
Sharpe Ratio (New Clients)	.603	.677	.074	2.07
Sharpe Ratio (Existing Clients)	.548	.545	-.003	-.13
Panel C: 36 Months	**Pre-2018**	**Post-2018**	**Change**	**t-statistic**
Sharpe Ratio (New Clients)	.596	.604	.008	.21
Sharpe Ratio (Existing Clients)	.540	.531	-.008	-.37
Panel D: 30 Months	**Pre-2018**	**Post-2018**	**Change**	**t-statistic**
Sharpe Ratio (New Clients)	.655	.747	.092	2.26
Sharpe Ratio (Existing Clients)	.575	.582	.007	.30
Panel E: 24 Months	**Pre-2018**	**Post-2018**	**Change**	**t-statistic**
Sharpe Ratio (New Clients)	.342	.437	.095	2.84
Sharpe Ratio (Existing Clients)	.239	.253	.014	.77

This Table displays Sharpe ratios for the portfolios of different groups of clients, both before and after the 2018 change in advisor incentives. Existing clients are defined as those joining the firm before June 2017 and remaining with the firm after 2018. New clients in the pre-2018 period are defined as those joining the firm in the six months after June 2017. New clients in the post-2018 period are defined as those joining the firm in the six months after March 2018. The portfolios of existing clients are computed using their average holdings in the six months after June 2017 (for the pre-period) and after March 2018 (for the post-period). The portfolios of new clients are computed using their average holdings in the three months after joining the firm. The Sharpe ratios are calculated using the same returns and variance-covariance matrix, regardless of the portfolio on which it is calculated. In each panel, the returns and variance-covariance matrix are calculated using different horizons. In Panel A we use the 48 months between the June 2013 to June 2017 period. In Panels B, C, D and E we use horizons of 42, 36, 30 and 24 months respectively, all ending in June 2017. The portfolios are constructed at the advisor level, grouping all clients of the same advisor together.

TABLE A8 - QUANTIFYING CLIENT UTILITY LOSS

Assumed r_f	**0%**	**.5%**	**1%**	**1.5%**	**3%**	**5%**
Computed						
γ	1.23	1.18	1.14	1.09	.95	.76
α	1.42	1.40	1.37	1.35	1.29	1.21
		Panel A: New Clients				
$\overline{Loss}^{Pre2018}$	9.36%	8.75%	8.16%	7.83%	6.50%	5.30%
$\overline{Loss}^{Post2018}$	5.17%	4.85%	4.56%	4.38%	3.85%	3.31%
$\Delta\overline{Loss}$	4.18%	3.91%	3.59%	3.46%	2.65%	1.99%
		Panel B: Existing Clients				
$\overline{Loss}^{Pre2018}$	7.16%	6.37%	5.77%	5.20%	3.91%	2.81%
$\overline{Loss}^{Post2018}$	5.61%	5.18%	4.81%	4.46%	3.48%	2.70%
$\Delta\overline{Loss}$	1.55%	1.19%	.96%	.74%	.43%	.11%

This Table shows the estimated client utility loss before and after the change in compensation policy implemented in January 2018 due to the enactment of MiFID II. Clients with the same advisor are aggregated to a client group by adding the investments in each fund. Investments in all external products are aggregated into three groups: (a) all external mutual funds, (b) all stocks, and (c) all fixed-income products. We define new clients in the pre-2018 period as those that join the firm in the six months before November 2017 and new clients in the post-2018 period as those that join the firm in the six months after March 2018. We then use their average holdings in the three months after joining to calculate their portfolio compositions. We define existing clients as those joining the firm at any point before June 2017 and remaining active in the post-2018 period. We treat the average holdings in the six months after March 2018 as the portfolios of the existing clients in the post-2018 period. For symmetry, we use the average holdings in the six months before November 2017 as the portfolios of the existing clients in the pre-2018 period. Since we need to estimate γ and α jointly, we take a recursive approach: we start with an α of zero to estimate the value of γ; we then use the estimated γ to derive a new estimate for α. We keep iterating this two-step procedure until arriving at a fixed-point solution for both γ and α. Given these parameters, we then quantify clients' utility loss both before and after January 2018. We aggregate clients with the same advisor to a client group (by summing up their investment in each internal fund), and estimate the expected utility loss at the advisor level.

TABLE A9
EFFECT OF THE SHOCK TO THE ADVISOR'S OVERALL COMPENSATION ON THE SHARE OF TOTAL FIRM INVESTMENT DEVOTED TO THE INTERNAL FUNDS

Dep. Var. = Share in Internal Funds	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Average Fee Increase X Post	.023				
	(.028)				
S.D. Fee Change X Post	.128				
	(.119)				
Average X Post X Financial Knowledge		-.003			
		(.06)			
S.D. X Post X Financial Knowledge		.264			
		(.203)			
Average X Post X Financial Education			.155*		
			(.081)		
S.D. X Post X Financial Education			.178		
			(.196)		
Average X Post X Financial Profession				.096	
				(.096)	
S.D. X Post X Financial Profession				.05	
				(.222)	
Average X Post X Share External					-.031
					(.035)
S.D. X Post X Share External					.099
					(.15)
Double Interactions	No	Yes	Yes	Yes	Yes
Client Fixed Effects	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes

This table displays estimates of regressions of the share invested in the internal funds as a function of measures to the shock to the advisor's overall compensation structure. The dependent variable is calculated as follows. We compute the total investment through the firm, which is the sum of the investment in the firm's internal funds and the investment in the external products through which the firm acts as a broker. The dependent variable is the share of this total investment that is devoted to the internal funds. The first independent variable is the *average* (simple average over all the sample funds) increase in the trailer fee experienced by the advisor in January 2018. The second independent variable is the standard deviation (taken over all the sample funds) of the change in the trailer fee experienced by the advisor in January 2018. Both independent variables are interacted with the post January 2018 dummy. In columns (2)-(5) these two interactions are further interacted with measures of client sophistication, such as a financial knowledge dummy, a financial education dummy, a financial profession dummy and the share invested in external products at the beginning of the sample period. Columns (2)-(5) include all double interactions. The estimating equation is:

$$ShareInternal_{ct} = \phi(Increase_{a(c)} \times Post_t) + \pi(SD_{a(c)} \times Post_t) + \beta_c + \kappa_t + \omega_{ct},$$

The subscripts are c for client, a for advisor and t for month. The unit of observation is a client/month combination. The regressions include client fixed effects and month fixed effects. Standard errors are clustered at the advisor level. N= 239,275; Advisors=164.

TABLE A10: FINANCIAL ASSETS OF HOUSEHOLDS HOLDING FUND INVESTMENTS. EVIDENCE FROM EFF SURVEY

Panel A: Financial Assets Held by EFF Fund Investors (Share of Total Financial Assets)

	Cash/Payment Accounts	Non-Payment Accounts	Listed Stocks	Other Equity	Fixed-Income Securities	Pension & Life Insurance	Managed Accounts	Other Financial Assets
Mean	0.324	0.148	0.081	0.016	0.007	0.159	0.014	0.029
Median	0.205	0.000	0.000	0.000	0.000	0.006	0.000	0.000
SD	0.314	0.252	0.170	0.090	0.055	0.241	0.086	0.113

Panel B: Within-household Correlation Between Changes in Investment Funds and Financial Assets

	Δ Share Cash/Payment Accounts	Δ Share Non-Payment Accounts	Δ Share Listed Stocks	Δ Share Other Equity	Δ Share Fixed-Income Securities	Δ Share Pension & Life Insurance	Δ Share Managed Accounts	Δ Share Other Financial Assets
Δ Share Inv Funds	-0.144*	-0.138*	-0.017	-0.030	-0.003	-0.047*	-0.056***	-0.006
	(0.064)	(0.064)	(0.014)	(0.016)	(0.004)	(0.021)	(0.016)	(0.008)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Δ log Gross Wealth	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Δ log HH Income	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Δ HH characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Data come from the 2011, 2014, 2017, and 2020 waves of the Spanish Survey of Household Finances (EFF). The sample includes only households with positive investment in mutual funds in at least one period. **Panel A:** N observations= 5651. N of houseuholds = 2688. Each row reports the mean, median, and standard deviation of the share of each financial asset (column) relative to the household's total financial investments. Total financial investments are defined as the sum of all asset types listed in the columns plus mutual funds. Notice that shares are first computed at the household level and then averaged across households, therefore mean shares do not sum to one. **Panel B:** N observations= 4731. N of houseuholds = 1762. Each column reports a separate equation from a seemingly unrelated regression (SUR) system. The dependent variable is the change in the share (relative to total gross wealth) of the corresponding asset category. The main regressor of interest is the change in the share of mutual funds over gross wealth. Additional controls (not reported) include changes in log gross wealth, log household income, household size, number of employed household members, and year fixed effects. Observations with changes in mutual fund share greater than 80 percentage points are excluded. Standard errors are clustered at the household level.