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The double bottom line of microfinance: A global comparison between conventional and Islamic microfinance

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ABSTRACT

Conventional microfinance institutions (MFIs) can promote financial inclusion, but they also prompt ethical concerns regarding the social consequences of commercialization and high interest rates. Islamic MFIs, which adhere to Sharia's prohibition of *riba* (usually interpreted as a ban on interest), present an alternative. Differences between conventional and Islamic MFIs in terms of outreach and financial sustainability remain underexplored; no comprehensive data set details Islamic MFIs either. With new data, collected with a global survey, the authors construct a unique panel of 543 conventional and 101 Islamic MFIs, operating in Islamic and non-Islamic countries. These data suggest that the market for Islamic microfinance is more important than previously recognized, has grown in recent years, and is likely to continue growing in every region of the world. Statistical comparisons, using various estimation techniques, regarding the outreach and financial performance of Islamic and conventional MFIs also reveal that the breadth and depth of Islamic MFIs exceed those of conventional MFIs, though conventional MFIs achieve stronger financial performance. This latter result is not robust though.

1. Introduction

Microfinance institutions (MFIs) generally strive to generate positive social impacts while simultaneously delivering sound financial performance to achieve a "double bottom line." By the end of 2017, 981 MFIs had submitted performance reports to the Microfinance Information Exchange (MIX Market), which revealed an estimated US$114 billion in loan volume and 139 million customers (Valette & Fassin, 2018). That is, this sector clearly has expanded to comprise a vast variety of organizations, which appear heterogeneous in their approaches to achieving this dual mandate. In response, a debate has cropped up, regarding which *types* of MFIs may be most successful in realizing both objectives (e.g., Armendáriz & Morduch, 2010; Banerjee, Karlan, & Zinman, 2015; Morduch, 2016). Some studies propose an influence of religion, such as when Mersland, DÉspallier, and Supphellen (2013) argue that Christian-based MFIs earn lower profits but also incur lower funding costs than conventional MFIs. The specific financing practices adopted by Islamic MFIs, such as interest-free forms of financial access, also might allow for greater outreach but require more resources to manage, relative to conventional microfinance (Visser, 2013). To the best of our knowledge, rigorous comparisons of conventional and Islamic MFIs, in terms of outreach and financial performance measures, and thus their ability to achieve the double bottom line, are lacking.

The question of whether conventional and Islamic MFIs perform differently is particularly relevant, considering the increasing interest in MFIs that offer products and services compliant with Islamic financial principles (Abedifar, Molyneux, & Tarazi, 2013).[1] A large proportion of the world's poor (700 million in 2013; World Bank, 2013) live in Muslim-majority nations, sparking interest in Islamic microfinance as a financial outreach tool. Even MFIs that previously offered only conventional microfinance products have started offering Islamic versions, marketing them as effective tools to facilitate and encourage small businesses (Ahmed, 2002). Yet Islamic MFIs differ markedly from conventional MFIs on several key

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[1] The global financial crisis of 2007–2008 raised interest in Islamic finance in general and Islamic microfinance in particular, because banks operating according to Islamic principles exhibited greater resilience to the crisis than their conventional counterparts. Global Islamic finance assets in 2017 accounted for more than US$2.4 trillion (Mohamed, Goni, & Hasan, 2018).

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dimensions, such as their sources of financing, investment and product portfolios, and management.[2] For example, high interest rates in the conventional MFI sector, in addition to being criticized as unethical (Hudon & Sandberg, 2013), conflict with Islamic prohibitions on microfinance products that involve paying or receiving *riba*.[3] Conventional, for-profit MFIs charge significantly higher interest rates when markets are less competitive (Baquero, Hamadi, & Heinen, 2018), and several conventional MFIs have been accused of acting like loan sharks, not only charging extremely high interest rates but also using aggressive collection methods (Boatright, 2014).

To investigate the possible trade-offs that Islamic MFIs confront in pursuing a double bottom line, we therefore construct a novel data set that reflects a comprehensive, global mapping of Islamic microfinance service providers. Using an online survey that we sent to all MFIs reporting to MIX Market, we identify MFIs currently providing microfinance products in line with Islamic principles, as well as those that plan to provide such products in the future. This classification is novel, in that it relies on direct survey questions about product offerings. We then align our findings with databases provided by the microfinance network for Arab countries, Sanabel (2012) and the Islamic Banking Database (2014), which establishes an MFI classification that is more comprehensive than previous approaches, in terms of the regions covered and number of Islamic MFIs included. We thus create a detailed, consistent map of the supply and demand sides of the market for Islamic microfinance products, according to global distribution trends. In total, we identify 644 MFIs by type and specify 101 of them, based in 33 countries that can be classified as Islamic MFI providers. These comprehensive data suggest that the market for Islamic microfinance is more important than is generally acknowledged, and its recent growth appears likely to persist, in every geographical region.

Using this newly constructed data set, we also undertake a comparison of the performance of conventional MFIs and Islamic MFIs, according to the dual objectives of social benefits and financial performance. Fan, John, Liu, and Tamanni (2019) compare Islamic and conventional MFIs too, using a sample of 300–600 observations, depending on the outcome variable, containing 316 MFIs. For this statistical analysis, we expand the sample to approximately 5000 observations, including 644 MFIs.[4] The analyses suggest that Islamic MFIs outperform conventional MFIs in terms of outreach, but conventional MFIs might perform better financially. This latter result is not robust though, which might reflect the endogeneity problems that affect our results, despite our best efforts to reduce possible sample selection problems by using cross-sectional, panel, and instrumental variable regression techniques.

In Section 2, we outline the main characteristics of and products offered by Islamic MFIs, along with a review of literature pertaining to the social and financial performance of MFIs. We also develop some testable hypotheses for our quantitative analyses. Section 3 presents the variables for our empirical analysis, provides some motivational statistics for our main analysis, and then details the empirical methodology. After we outline the results, according to our newly constructed data set and regression analyses, in Section 4, we conclude in Section 5.

[2] Differences in financial sustainability also might reflect distinct sources of funding, such as funding by Islamic charities and donations or other borrowers' contributions, which are more prevalent in Islamic MFIs.

[3] Many studies use interest and *riba* interchangeably, but they are not exactly the same (Ugi, 2018). It is more accurate to state that Islam prohibits *riba*, not interest. Yet the ban on *riba* is widely interpreted as a ban on interest by *fiqh* scholars who specialize in Islamic jurisprudence.

[4] Other comparative studies of Islamic and conventional MFIs offer conflicting results, based on a more restricted set of Islamic MFIs, such as Widiarto and Emrouznejad (2015) and Abdelkader and Salem (2013).

2. Literature review and hypotheses development

2.1. Features of Islamic microfinance

Islamic microfinance offers an alternative to conventional microfinance for meeting the financial needs of the poor and financially excluded (Karim, Tarazi, & Reille, 2008). The two microfinance forms differ considerably from an operational perspective (Ahmed, 2002). Even if some fundamental similarities apply to the financial instruments or techniques, the products and services provided by Islamic MFIs are free of particular elements (Obaidullah, 2008), because their business activities must adhere to *halal* (permissible) principles. For example, both conventional and Islamic MFIs use equity and debt-based financing, but they operationalize the instruments differently. Weill (2020) proposes a summary of four main principles of Islamic (micro-)finance:

(1) Interest is forbidden.
(2) Lenders are rewarded through profit sharing, though the most popular Islamic microfinance products do not reflect conventional profit-and-loss sharing principles, as we discuss subsequently.
(3) The MFIs cannot finance activities considered sinful by Islam, such as *maysir* (gambling) (Chong & Liu, 2009), alcohol, or borrowing and lending to conventional MFIs that charge interest.
(4) Contract terms should be entirely clear and eliminate any contractual uncertainty, due to the prohibition of *gharar* (uncertainty).

The Sharia-compliant financial products that Islamic MFIs offer can be broadly categorized into three types: (1) equity financing instruments, such as *mudaraba* and *musharaka*; (2) credit or debt financing instruments, including *ijara*, *istisna*, *murabaha*, *qard e hasan*, and *sala'm*; and (3) other types of microfinancing, such as asset-building products, typically in the form of saving accounts (e.g., *wadiah*), investment deposits, or mutual insurance schemes (e.g., *micro-takaful*). We address the first two categories in more detail next but exclude the third category as this category is not relevant for the analysis in this paper.

2.1.1. Equity-like instruments

Equity financing relies on profit-and-loss sharing (PLS) arrangements, rather than interest-based contracts, between an Islamic MFI and its clients, to conform with Islamic principles (Khan & Mirakhor, 1992). For example, under a *mudaraba* or trustee financing contract, the MFI is the investor (financier), and the MFI's client manages the enterprise. If the business generates profits, the funding parties split the gains according to some predetermined rule (Visser, 2013). Thus, the profit shares are predetermined, but the profits are unknown in advance (Weill, 2020). If the business incurs a loss, it is borne exclusively by the Islamic MFI, but the entrepreneur (i.e., client) receives no compensation. Under an equity partnership *musharaka* contract, both the MFI and the client instead contribute capital and share profits according to a predefined rule, and they also jointly manage the business. Profits are negotiated freely; losses are covered according to the capital contributions of the MFI and the entrepreneur. *Mudaraba* is thus closer to a limited partnership, whereas *musharaka* is similar to a business model involving equity stakes with controlling rights.

Although a strict application of PLS principles reduces the risk of insolvency for an Islamic MFI, the shareholders' risk also might transfer to depositors, in form of more volatile returns (Visser, 2013). In practice, Islamic banks often stabilize the profit distributions to depositors, but Islamic (and conventional) MFIs cannot accept deposits (or savings) to begin with, and they often are not subject to regulations by a Central Bank or other monetary authority. Moreover, PLS contracts may increase information asymmetry problems, relative to debt-based interest rate contracts (Weill, 2020). In particular, adverse selection problems probably grow more acute with PLS contracts. Borrowers with low profit expectations prefer a PLS contract over an interest-based one, because the amount they must share with the lender (i.e., a share of their small profits) under a PLS contract probably is lower than a fixed interest payment. But borrowers earning higher profits likely seek an interest-based contract so they can pay a fixed payment, lower than the share of their profits. Moreover, interest-based contracts incentivize borrowers to work harder to earn high returns, because they still pay the same, fixed amount, regardless of their profits. In contrast, a PLS contract requires a higher payment if they earn more, so borrowers might lack strong enough incentives to put forth stringent effort. Such a scenario is likely to lead to moral hazard problems.

2.1.2. Debt-based instruments

Debt-based instruments instead do not align with PLS principles (Shahinpoor, 2009), so they may evoke higher risk for the borrower, because repayment does not depend on the borrower's profits (Weill, 2020). For example, *ijara* is a lease purchase; the MFI allows a client to use an asset it possesses, for a certain price and period.[5] With each payment, the lessee moves closer to a purchase and transfer of ownership of the leased asset. Unlike traditional leasing though, all risks are borne by the MFI, including any impairment or damage to the leased asset caused by factors outside the client's control, such as weather events. These terms are stated in advance.

Istisna is an exchange contract that defers payment and delivery of the product; the MFI might produce goods itself or buy them from a third party, then deliver them to the end customer (i.e., client). This contract refers to goods that have yet to be produced, such as a building or road. The end customer might pay when the contract is signed or at subsequent stages in the manufacturing process. Instead, *murabaha* is a goods-financing contract, such that the MFI acquires a requested product and resells it to the client for its cost plus a markup to cover any service costs. It facilitates the purchase and resale of commodities in rural areas in particular (Wilson, 2007). *Murabaha* can evoke high costs, often higher than conventional financial products, because the Islamic MFI must physically handle the goods, ensure they are properly stored, and insure them (Visser, 2013). It also involves two sales transactions and thus potentially two tax payments, though this issue should not be a concern in relation to value-added taxes (VAT). The VAT or other ad valorem tax on conventional sales that require interest payments by definition will be lower than the tax imposed on a *murabaha* sale though, in which a markup gets added to the sales price.[6]

Qard e hasan is an interest-free loan. The borrower repays the principal, with no return, reflecting the Islamic precept that Muslims should help those in need, such as by supporting rural households or giving prospective entrepreneurs a chance to start their business (Abdul Rahman, 2007; Obaidullah, 2008; Wilson, 2007). A small fee of approximately 0.5 percent may be charged to cover expenses.

Finally, *sala'm* is a forward sale, mostly used for agricultural financing. The quality, quantity, time, and price of the goods to be purchased must be fully specified, leaving no ambiguity (Dhumale & Sapcanin, 1999; Obaidullah, 2008). The goods included in these contracts cannot be gold, silver, or currencies.

2.2. Social and financial performance of MFIs

Microfinance institutions, both conventional and Islamic, have social and financial objectives. On the one hand, MFIs aim to reduce poverty by providing financial services to poor households that have been excluded from the formal financial system. On the other hand, the MFIs themselves aim to achieve financial self-sufficiency, without the need for subsidies (Tulchin, 2003). Achieving both objectives simultaneously is referred to as attaining the microfinance promise (Morduch, 1999) or double bottom line (Armendáriz & Labie, 2011). In practice, it remains difficult to reach both objectives, which even may be subject to a trade-off. According to financial systems (Robinson, 2001) or self-sustainability (Schreiner, 2002) approach, social performance and financial sustainability can go hand-in-hand, because reaching more customers should create economies of scale. If financially sustainable MFIs attract more funds, it could increase their ability to serve more poor people. A poverty lending (Robinson, 2001; Schreiner, 2002) perspective instead implies the necessary trade-off between social performance and financial sustainability, because providing financial services to the poor is expensive and can persist only by MFIs that receive subsidies (i.e., not financially self-sustainable). The high costs of lending primarily stem from the transaction costs, in that poor people often live in remote areas, and high fixed costs, even for small loan amounts. Theoretically, it is not clear whether social and financial objectives trade off or are compatible; empirical studies appear necessary to address this debate.

Different contributions from empirical microfinance literature also inform this discussion. In particular, some studies examine the social and economic impacts of microfinance on end-users; recent studies using randomized controlled trials tend to offer strong criticisms. For example, Banerjee et al. (2015) conclude, from a study across eight countries, that microcredit fails to induce transformative effects or raise households out of poverty. Dahal and Fiala (2020) instead argue that prior studies are severely underpowered, such that it is impossible to establish whether and how microcredit affects welfare. With their non-experimental study in Sierra Leone, Garcia, Lensink, and Voors (2020) provide evidence that microcredit offered through group lending systems helps people release their internal psychological constraints and develop aspirational hope, which may provide a foundation for increased welfare in the future. Across these contrasting views though, a general consensus indicates that microfinance is not a panacea. In particular, the social impact of microcredit appears lower than early predictions suggested and probably cannot lift large segments of poor populations out of poverty, though that pessimistic conclusion may refer mainly to microcredit, not necessarily the wider range of microfinance activities, such as microsavings and microinsurance. Furthermore, various groups of vulnerable people might respond to microfinance activities in distinct ways, as implied by recent survey research by Hansen, Huis, and Lensink (2020), Hermes and Lensink (in press), and Lensink and Bulte (2019).

The disappointing results of microcredit also have induced another stream of research that seeks tactics for improving its impact (Lensink & Bulte, 2019). One option is to rethink the product design; whereas traditional microcredit involves short-term, group loans with rigid contract terms, more flexible repayment terms, such as might be achieved through longer grace periods (Field, Pande, Papp, & Rigol, 2013), could increase the impact of microcredit. Another approach expands on microfinance, to go beyond providing credit and also offer varied financial and non-financial services, such as gender-based and business training. Such offerings are broadly referred to as microfinance-plus (Garcia & Lensink, 2019). Bulte, Lensink, and Vu (2017), with an experimental study in Vietnam, suggest that combining credit with

[5] Here, we refer to a lease to buy (*ijara wa iqtina*, also known as *ijara muntahia bi tamleek*), not an operational lease.

[6] We thank an anonymous referee for noting this point.

business training may enhance the impacts. However, both more flexible contract terms and microfinance-plus activities also have financial consequences and may demand additional subsidies, with detrimental impacts on the financial self-sufficiency objectives.

The pursuit of this second, financial objective seemingly has prompted increasing commercialization of conventional microfinance, which critics allege has created mission drift, increased consideration of wealthier clients, the exclusion of poor and female borrowers (Cull, Demirgüç-kunt, & Morduch, 2007), and a shift toward more individual lending. Notably, de Quidt, Fetzer, and Ghatak (2018a) provide theoretical and empirical evidence that commercialization in conventional microfinance leads to greater competition and shifts away from non-profit group lending and toward for-profit individual lending. Commercialization induces greater competition too, which arguably should increase the funds available, such that it could have positive effects. With a simulation exercise, de Quidt, Fetzer, and Ghatak (2018b) predict that the negative effects of monopolistic for-profit lending, due to commercialization, are almost entirely compensated for by the results of increased competition. Thus, the ultimate influence of commercialization is ambiguous, and in practice, the MFI's internal organization appears important in determining these effects. Churchill (2019) provides empirical evidence that non-profit MFIs are more socially driven than for-profit ones, which instead may be more concerned about financial returns, perhaps at the cost of their social objective (Hermes & Lensink, in press).

Another closely related stream of literature explicitly focuses on the supply side. That is, rather than investigating the impact of microfinance on end-users by gathering individual-level data, these studies address the MFIs themselves, with data at the MFI level. Hermes and Hudon (2018) provide a systematic review of such studies, but for our purposes, we note an interesting point these studies raise, pertaining to the trade-off between social outreach and financial sustainability. From a supply-side perspective, financial sustainability implies that MFIs' activities do not result in losses over time, such that they no longer need subsidies but still can continue to provide microcredit (Balkenhol, 2007; Quayes, 2012). Such financial sustainability can be measured with standard financial ratios such as the return on equity (ROE) or the return on assets (ROA), though some researchers use the operational self-sufficiency of MFIs, which reflects whether they can cover their costs with revenues, or their financial self-sufficiency, which indicates whether they can operate without ongoing subsidies, soft loans, or grants. Finally, studies that use data envelopment or stochastic frontier analyses tend to measure (financial) efficiency (e.g., Caudill, Gropper, & Hartarska, 2009; Hermes, Lensink, & Meesters, 2011; Servin, Lensink, & van den Berg, 2012; for a meta-analysis, see Fall, Akim, & Wassongma, 2018).

From a supply-side perspective, outreach is the representation of the social value created by MFIs, which can be measured by two dimensions: depth and breadth (Navajas, Schreiner, Meyer, Gonzalez-Vega, & Rodriguez-Meza, 2000; Schreiner, 2002). The breadth of outreach reflects how many people the MFI serves, reflecting its coverage in terms of the number of clients served. The depth of outreach instead indicates whether an MFI serves the poorest segments of the population (Brau & Woller, 2004; Schreiner, 2002), generally measured by either the average loan size scaled by the gross domestic product (GDP) per capita of the focal country or by the ratio of female to the total number of borrowers. Unlike financial performance, which is relatively easy to quantify using available, validated finance and accounting measures, debate continues about how best to measure social performance. DÉspallier and Goedecke (2020) offer a survey discussion and detail some disadvantages of standard outreach indicators; in particular, outreach cannot be identical to social performance and at best is a subdimension of a broad range of social performance indicators. Nor does outreach reflect the overall impact of microfinance, which refers to the ultimate influence that financial services have on people's welfare. Greater outreach, implying that the MFI has provided financial services to more people or proportionally more to the poorest people, might lead to positive impacts but does not do so inevitably. Even further, we cannot confirm that average loan size, a commonly used measure of breadth, has any relationship with poverty levels, because MFIs might cross-subsidize expensive, small loans with profitable, larger loans, which produces a higher average loan size (Armendáriz & Szafarz, 2011). Alternatively, increased average loan sizes may stem from demand-side factors related to the type of clients (Morduch, 2000) or reflect a progressive lending system in which credit limits increase over time, conditional on repayments of previous loans. Overall then, outreach indicators provide, at best, only an imperfect indication of MFIs' social performance.

Accordingly, empirical supply-side studies offer mixed results. Some studies suggest a negative relationship between outreach and financial sustainability (Cull et al., 2007; Hartarska, Shen, & Mersland, 2013; Hermes et al., 2011; Louis & Baesens, 2013); others find no trade-off (Adhikary & Papachristou, 2014; Louis, Seret, & Baesens, 2013). A few studies propose that the likelihood of a trade-off is contingent on factors such as the representation of stakeholders on boards of MFIs (Hartarska, 2005), gender diversity in the board (Hartarska, Nadolnyak, & Mersland, 2014), or loan methodology (Tchakoute-Tchuigoua, 2012). Churchill (2019) instead points to the type of outreach as an important contingency, such that a trade-off may arise between financial sustainability and depth, but complementarity marks the link between financial sustainability and breadth. Churchill also shows that for-profit MFIs outperform non-profit MFIs in terms of financial sustainability and breadth of outreach, but not on the depth of outreach, which reiterates the likely importance of organizational structure. Finally, with a comprehensive meta-analysis of relevant literature, Reichert (2018) simply concludes that there is no definitive answer to the question of whether MFIs can achieve both goals simultaneously.

2.3. Hypotheses development

Using insights from our review of prior literature, which relates mainly to conventional MFIs, we seek to establish some predictions regarding how conventional and Islamic MFIs might compare with regard to the trade-off. We do not aim to derive new theory to explain the differences between the two types of MFIs; rather, we try to establish testable hypotheses.

With regard to social performance, we deliberately restrict our predictions to differences in outreach, rather than social impact; our research methodology (in line with prior supply-side studies) cannot identify impact, which would require data from end-users. Thus, the comparison focuses on the amount (breadth) and type (depth) of borrowers served by the two types of institutions. Both conventional and Islamic MFIs aim to provide financial access to borrowers neglected by mainstream financial institutions (Cull et al., 2007; Kleynjans & Hudon, 2016; Strøm, DÉspallier, & Mersland, 2014). Among conventional MFIs, non-profit versions still exist, though several developments make them less prominent, as detailed by de Quidt et al. (2018a), including a broad shift from non-profit to for-profit MFIs, increasing competition among the growing numbers of MFIs in each country, and the enhanced importance of individual lending at the expense of joint liability group lending. According to Churchill (2019) findings, these three trends seem likely to lead to greater breadth of outreach but decreased depth among conventional MFIs. For example, rising interest rates and heightened penalties for non-repayment (Dehejia, Montgomery, & Morduch, 2012) imposed by for-profit

MFIs likely lead to *involuntary* exclusions of the poorest borrowers from conventional MFIs. In contrast, Islamic MFIs explicitly integrate a religious foundation for their operating principles, which means they are barred from offering products that involve interest (Abedifar et al., 2013) and also try to avoid high commissions or fees (Beck, De Jonghe, & Schepens, 2013). Borrowers of Islamic MFIs thus may be less likely to confront high borrowing costs or *involuntary* exclusion. Moreover, borrowers who strictly adhere to Islamic principles are de facto unable to borrow from conventional MFIs, which do not adhere to Sharia. In this sense, conventional MFIs may encounter more *voluntary* financial exclusion, which may affect the breadth and depth of their outreach. The poorest members of the population often adhere strictly to Sharia, due to social and religious norms (El-Gamal, El-Komi, Karlan, & Osman, 2014), so we predict that voluntary exclusion may primarily affect the depth of outreach, though this assertion is not clear ex ante. More relevant for the breadth of outreach, Islamic MFIs are not allowed to borrow from or lend to conventional MFIs, which may induce liquidity problems (Weill, 2020). However, such limitations on breadth also could be compensated for by expanded access to other funding sources, such as Islamic charities and donations or contributions from other borrowers. Therefore, we hypothesize that Islamic MFIs perform, on average, better on outreach than conventional MFIs, especially in terms of depth, whereas the outcomes for breadth are less clear, due to liquidity concerns.

Turning to financial sustainability, we offer several reasons Islamic MFIs may be likely to underperform financially relative to conventional MFIs. First, their operational and administrative costs likely are higher (El-Zoghbi & Tarazi, 2013). Notably, Islamic MFIs frequently offer non-PLS *murabaha* contracts, tied to some asset (e.g., property, plant, equipment). The need to transfer such an asset demands substantial operational costs, far more than managing a cash distribution. *Murabaha* also implies two sales transactions instead of one, along with a higher sales price that integrates a markup (and thus higher taxes). Furthermore, it requires MFIs to store and insure the asset, with further increased costs. Another popular product is *qard e hasan* (El-Zoghbi & Tarazi, 2013), which is easier to administer than *murabaha* but still is not priced to cover all administrative and default costs. Second, even the PLS contracts probably lead to more adverse selection and moral hazard problems than interest-based contracts. Thus, for the (relatively small) group of Islamic MFIs that adopt PLS schemes, profits still may be lower than those earned by conventional MFIs. The relatively high costs of providing Sharia-compliant products may explain why the development of Islamic microfinance has lagged; Islamic microfinance products still serve less than 1 percent of borrowers (El-Zoghbi & Tarazi, 2013). Noting the generally higher operational costs and lower pricing of Islamic financial products, relative to conventional microfinance, we hypothesize that Islamic MFIs are less profitable than conventional MFIs.

3. Data, model specification, and variables

3.1. Sample construction

To identify MFIs that offer Sharia-compliant products, we conducted a web survey in 2016 (for more details, see Appendix A), using invitation emails sent to key staff members of the 2,544 MFIs that report to MIX Market.[7] The survey contained questions about whether the MFI offered financial products in line with Islamic principles, as well as the types of conventional and Islamic financial products offered. We combined the results of our survey with information gathered from two, more limited databases, namely, the Sanabel (2012) and the Islamic Banking Database (2014).[8] For conventional MFIs, we also asked about plans to include Sharia-compliant products in future portfolios.

We combine our global survey data (collected in 2016) with existing (financial and outreach-related) information for the years 1999–2016, obtained from MIX Market. For some variables, we also turned to other, existing data sources. Specifically, we obtain country-level information about the percentage of the population that is Muslim from Kettani (2010).[9] For information about the official state religion, we rely on a detailed report by Barro and McCleary (2005), updated with other publicly available sources.[10] We obtain GDP data from the World Bank (http://data.worldbank.org). The final sample of MFIs that completed our survey consists of 644 MFIs in 86 countries for the period 1999–2016, around 11% of which are Islamic MFIs.

3.2. Model specification

One of the main challenges of comparing outreach and financial performance by Islamic versus conventional MFIs relates to endogeneity biases. That is, Islamic and conventional MFIs are not randomly distributed over different countries, and some (probably the most poor) Islamic borrowers are religiously prohibited from borrowing from conventional MFIs. We thus cannot randomly assign potential borrowers, who might borrow from both types of MFIs, to either Islamic or conventional MFIs, and there is no clear-cut solution to this endogeneity issue.

To address our central question, we apply both cross-sectional and panel regressions, adopting several empirical approaches in an attempt to mitigate endogeneity concerns.[11] First, noting that the main independent variable of interest (whether an MFI is Islamic, *ISMFI*) is time-invariant, we start with two cross-sectional approaches, using the between-subjects estimator and a Fama-MacBeth regression.[12] These regressions (as well as those detailed subsequently) include approximately 10 additional independent variables that allow us to control for selection based on observable MFI characteristics (which we describe later in this section) to assuage concerns about omitted variable bias. Second, we also use a random-effects model and exploit the panel dimensions of our data; we expect the estimates to be more efficient than in our cross-sectional approach. Time dummies control for year effects. Third, to address the endogeneity of the Islamic MFI variable, we use an instrumental variables (IV) approach with two alternative

[7] The MIX Market database provides information about a global set of registered MFIs (www.mixmarket.com). Being listed indicates the MFI's willingness to comply with the data standards set by MIX Market, simply by the act of reporting data, yet these data suffer from the well-known self-reporting biases.

[8] In our data set of 101 Islamic MFIs, 89 were identified by our survey question; Sanabel (2012) and the Islamic Banking Database (2014) helped us identify 12 additional Islamic MFIs that report to MIX Market.

[9] We calculate the Muslim population for each period as $Population_{Future} = Population_{Present} x(1+i)^n$, where i is the growth rate and n is the number of years, which is 10 years for our study. For details, see Appendix B.1.

[10] We cross-checked the information with data from the Organisation from Islamic Corporation. Accessed from http://insct.syr.edu/wp-content/uploads/2014/08/OIC_Member_States.pdf.

[11] In contrast, Fan et al. (2019) only provide standard ordinary least square regressions for comparing conventional and Islamic MFIs

[12] Some MFIs that claim to be Islamic offer both Islamic and non-Islamic microfinance products. We follow standard practice and classify MFIs as Islamic if they offer both Islamic and non-Islamic microfinance products (e.g., Widiarto & Emrouznejad, 2015). Their financial statements do not report the data for Islamic and non-Islamic microfinance products separately, so it is not possible for us to differentiate the contribution and role of Islamic versus non-Islamic products offered by these MFIs.

instruments, though the choice of instruments (described subsequently) is limited by data availability. Fourth, we use an inverse probability weighting (IPWIV) estimator to control for non-response bias and non-random selection into the survey. The use of different estimation techniques may enhance confidence in the robustness of the results, though none of our identification strategies can fully resolve endogeneity issues, so our results should be interpreted as correlational, not causal.

In all our empirical models, we regress the measures of outreach and financial performance by an MFI *i* in country *j* (at time *t*, when we include the panel dimension), which we denote *y* on a time-invariant dummy variable that equals 1 if the MFI in question is Islamic, and 0 otherwise ($ISMFI_{ij}$), in addition to a series of control variables, denoted by *Z*, that (may) vary across MFIs, country, and time. The precise definitions of the dependent variables (outreach and financial performance) are in Table 4 and explained in greater detail in Section 4.3.1.

Because our main independent variable $ISMFI_{ij}$ is time-invariant, we start with a cross-sectional regression, and our first estimate uses a between-subject estimator, such that we run an ordinary least squares (OLS) regression on the group means (we denote this specification GROUP MEANS), as follows:

$$\bar{y}_{ij} = \alpha_0 + \alpha_1\, \overline{ISMFI}_{ij} + \gamma\, \bar{Z}_{ij} + \varepsilon_{ij}, \tag{1}$$

where y_{ij} denotes measures of either the outreach or financial performance of an MFI *i* operating in country *j*; α_0 is a constant; and ε_{ij} indicates mean-zero errors. In Eq. (1), all variables refer to means across the period from 1999 to 2016.

Then we employ a second cross-sectional approach, with two-step Fama and MacBeth (1973) regressions (FM). The first step estimates the following cross-sectional regressions for each year in our sample, from 1999 (period 1) to 2016 (period T), Eq. (2) :

$$\begin{array}{c} y_{ij,1} = \alpha_{0,\,1} + \alpha_{1,1} ISMFI_{ij} + \gamma_1 Z_{ij,1} + \ \varepsilon_{ij,1} \\ y_{ij,2} = \alpha_{0,2} + \alpha_{1,2} ISMFI_{ij} + \gamma_2 Z_{ij,2} + \ \varepsilon_{ij,2} \\ \vdots \\ y_{ij,T} = \alpha_{0,\,T} + \alpha_{1,T} ISMFI_{ij} + \gamma_T Z_{ij,T} + \ \varepsilon_{ij,T} \end{array}, \tag{2}$$

where all variables are defined as previously. The second step takes averages of the estimated α and γ coefficients computed in the first step and uses Fama and MacBeth (1973) adjusted t-statistics to test for the significance of the coefficients.

In addition, we estimate the effect of interest using panel regressions. For the time-invariant variable $ISMFI_{ij}$, we estimate a random effects model with the following form, Eq. (3):

$$y_{ij,t} = \alpha_0 + \alpha_1 ISMFI_{ij} + \gamma Z_{ij,t} + c_{ij} + \varepsilon_{ij,t}, \tag{3}$$

where c_{ij} is the individual unobserved (random) effect of MFI *i* in country *j*, and $\varepsilon_{ij,t}$ is a mean-zero error term.

As we have argued, the Islamic MFI treatment variable is likely endogenous, because MFIs *choose* to offer Islamic products. Thus, we also use a random effects instrumental variable estimator (REIV). We leverage the percentage of Muslims *(PMP)* and whether Islam is a state religion *(Islstate)* in the country where the MFI operates as instruments for *ISMFI*. These two variables should correlate closely with the extent to which an MFI operates in line with Islamic lending principles. Yet it is unlikely that these variables influence the outreach or financial performance of MFIs directly, other than through the *ISMFI* variable. The first-stage results for the IV regression for the "Average Loan Balance per Borrower/GNI per Capita" are in Table C.1 in Appendix C.[13]

Finally, the sample includes only those MFIs that responded to our survey, so we use an inverse probability weighting estimator to control for potential sample selection caused by non-responses (Seaman & White, 2013). Briefly, this procedure works as follows: We use a logit model to predict the probability that an MFI responds to the survey, according to a set of independent variables (year dummies, dummy variables for the legal status of the MFI, the variables previously included in the Z vector; see Table C.2.1 in Appendix C). The inverse values of these predicted probabilities then serve as weights in the subsequent regressions (of the determinants of outreach and financial performance), such that observations with characteristics similar to those MFIs that did not respond to our survey take higher weights. We report results for which we combine the inverse probability weighting estimator with the IV approach.[14] (We also conducted these estimates without instruments, and those results are available on request.)

4. Empirical results

This section presents the results of our empirical analyses. We start by presenting summary statistics about the prevalence and geographic distribution of Islamic MFIs, based on our newly conducted survey. Then we offer new summary statistics regarding the most common forms of financial contracts used by Islamic MFIs. Finally, we present the regression results related to the impact of Islamic versus conventional MFIs on outreach and financial sustainability.

4.1. Global expansion of Islamic microfinance: mapping exercise

The values reported in this subsection derive from Table 1. We classify roughly 15.7% of the responding MFIs as Islamic: 101 MFIs in 33 countries, spread across all world regions, report that they offer Sharia-compliant products, whereas 543 MFIs exclusively offer conventional products. Of the 543 conventional MFIs that responded to our survey, 129 provide interest-free products, such as grants and loans.[15] Sudan (13 Islamic MFIs) and Pakistan (13 Islamic MFIs) host the highest numbers of Islamic microfinance service providers,[16] followed by Bangladesh (9), Indonesia (7), and Palestine (7). Table 1 also shows a rough estimate of the projected number of

[13] The first-stage results for the other outreach and financial performances indicators are very similar and can be obtained on request. Because our endogenous variable ISMFI is time-invariant, we cannot use a first-difference generalized method of moments (GMM) approach to identify ISMFI. In a system GMM approach, it would be possible to include (and identify) ISMFI. However, the first difference of ISMFI cannot be used as an instrument (it would disappear), so we cannot treat ISMFI as endogenous variable according to a system GMM approach. The only solution thus is to treat ISMFI as exogenous. Treating it as endogenous would require finding external instruments, as in our IV regression methods. Therefore, we prefer to use our method with external instruments, rather than GMM-based estimation techniques.

[14] The weighted instrumental regressions are estimated without random effects (normal OLS), because no available STATA programs can estimate weighted random effects models with instruments. However, we cluster standard errors at the MFI level. Because we are mainly interested in the coefficient for Islamic MFIs, this choice does not change the main results.

[15] In our survey, we directly asked about interest-free or Islamic microfinance product offerings, which helped distinguish Islamic interest-free MFIs from non-Islamic interest-free MFIs. We identified 230 interest-free MFIs, of which 129 are non-Islamic and 101 are Islamic MFIs. The non-Islamic MFIs that provide interest-free products are not considered Islamic for this analysis. The full questionnaire is available on request.

[16] This finding is not surprising: In Sudan, the entire financial sector is required to be Sharia-compliant by national law. Whereas it hosted few MFIs in 2006, serving only 9500 clients, Sudan more recently supported over 400,000 customers via Islamic MFIs (El-Zoghbi & Tarazi, 2013). Unlike in Sudan, both Islamic and conventional MFIs operate in Pakistan. However, since 2007, the State Bank of Pakistan has increased institutional support for Islamic microfinance.

Table 1
Worldwide Distribution of Islamic, Conventional, and Future Islamic MFIs.

Eastern Europe and Central Asia

Countries	No. of MFIs: ISMFIs	CMFIs	FISMFIs
Albania		2	
Armenia		3	
Azerbaijan		5	4
Bosnia and Herzegovina	2	6	2
Bulgaria		1	
Croatia		1	
Georgia		4	
Kazakhstan		6	
Kosovo	2	3	2
Kyrgyzstan	1	10	4
Macedonia		1	
Moldova		2	
Mongolia		3	
Montenegro		2	
Poland		2	
Romania		3	
Russia		8	
Serbia		2	1
Tajikistan		9	5
Uzbekistan		1	
Total	5	74	18

Latin America and the Caribbean

Countries	No. of MFIs: ISMFIs	CMFIs	FISMFIs
Argentina		2	
Bolivia		10	
Brazil		5	
Chile		2	
Colombia		19	1
Costa Rica		8	
Dominican Republic		8	
Ecuador		16	
El Salvador		7	
Guatemala		11	1
Haiti		3	
Honduras		16	
Mexico	1	9	1
Nicaragua		7	1
Panama		3	
Paraguay		2	
Peru	1	14	1
Uruguay		1	
Total	2	143	5

South Asia

Countries	No. of MFIs: ISMFIs	CMFIs	FISMFIs
Afghanistan	6		6
Bangladesh	9	31	17
Bhutan		1	
India	1	40	6
Nepal		10	1
Pakistan	13	11	17
Sri Lanka	1	8	3
Total	30	101	50

East Asia and the Pacific

Countries	No. of MFIs: ISMFIs	CMFIs	FISMFIs
Cambodia	1	9	2
China	1	2	2
Indonesia	7	5	12
Laos		2	
Malaysia	1		1
Myanmar		2	1
Guinea		2	1
Philippines	2	16	4
Vietnam		4	
Total	12	42	14

Sub-Saharan Africa

Countries	No. of MFIs: ISMFIs	CMFIs	FISMFIs
Benin	1	9	5
Burkina Faso		16	7
Burundi		3	
Cameroon	1	11	7
Central African Republic		1	
Congo, D.R.		6	2
Cote d'Ivoire	1	8	5
Ethiopia	2	6	6
Gabon		1	1
Ghana		19	3
Guinea		1	1
Kenya		6	2
Madagascar		4	
Malawi		7	1
Mali		8	1
Niger	1	4	3
Nigeria	1	13	1
Rwanda		6	
Senegal	2	11	8
Sierra Leone		1	
Somalia	1		1
South Africa		1	
South Sudan		3	1
Sudan	13		13
Tanzania		8	4
Togo		10	
Uganda		6	2
Total	23	169	74

Middle East and North Africa

Countries	No. of MFIs: ISMFIs	CMFIs	FISMFIs
Bahrain	1		1
Egypt	2	2	3
Iraq	6	5	9
Jordan	2	1	3
Lebanon	2	1	2
Palestine	7	2	7
Saudi Arabia	2	1	2
Syria	1	1	2
Tunisia		1	
Yemen	6		6
Total	29	14	35

Notes: This table shows the geographical distribution of Islamic, conventional, and future Islamic MFIs (denoted ISMFIs, CMFIs, and FISMFIs, respectively) across six global regions. To identify Islamic MFIs, we use three data sources; the main source was the survey conducted in 2016, but the Sanabel (2012) and the Islamic Banking Database (2014) were also consulted. The identification of conventional MFIs comes from our survey. For the group of future Islamic MFIs, we added available ISMFIs to CMFIs that indicated they intend to provide Islamic financial products in the future in our survey.

Table 2
Islamic financial products.

Islamic Financial Products	Percentage Provision	Percentage of Clients Using Products
Murabaha	75.8	47.6
Mudaraba/Musharaka	17.2	22.6
Qard e hasan	58.6	23.1
Sala'm	20.7	18.2
Other	24.1	73.5

Table 3
Comparing Islamic and conventional MFIs.

	Islamic	Conventional	p-Value
Clients			
Farmers	45.6	34.2	0.031
Salaried persons	12.3	17.2	0.25
Micro-entrepreneurs	40.9	53.5	0.043
Women	64.4	63.6	0.87
Clients below poverty line	45.2	43.4	0.78
Lending classification			
Rural	69.1	60.7	0.14
Group	53.1	48.9	0.59
Sources of funds for MFIs			
Donor agencies	48.2	33.8	0.13
Philanthropic donations	7.4	6.6	0.87
Charities	3.7	3.6	0.98
Government support	37	16.4	0.01
Waqf	3.7	4.4	0.86
Zakat Fund	7.4	0.4	<0.001

Notes: This table presents the difference between Islamic and conventional MFIs in terms of targeted clients, lending classification, and sources of funds, according to an equality of means test. Data come from our survey.

Islamic MFIs for our sample, calculated as a sum of the number of all current Islamic MFIs plus all conventional MFIs that indicated they intended to provide Islamic financial products in the future. These projections show that the shares of MFIs offering Islamic microfinance products are expected to grow across all regions (average of 1.3%), with the largest growth expected in Eastern Europe and Central Asia (average of 2.3%).[17]

This data set also highlights the growth achieved already by Islamic MFIs. Global market share (represented by financial revenue) has increased from US$1 million in 1999 to US$325 million in 2016, and the market size (represented by total assets) increased from US$9 million to US$1,827 million in the same period.[18] To put such growth in perspective, we compare this market size with that of the total assets of one big U.S. bank, JP Morgan Chase (2017): At the end of December 2017, it amounted to more than US$2.5 trillion. That is, on a global scale, the Islamic MFI sector is still small and concentrated, mostly in the Middle East. However, our survey results suggest the number of Islamic MFIs (and conventional MFIs offering Islamic products) will grow quickly, so this market share also is likely to increase considerably in the near future.

4.2. Characterization of the provision of Islamic financial products

Our survey results reveal some key features about the popularity, clientele, and funding base of the different instruments. The term "average" in this discussion refers to an average across MFIs.

First, equity instruments are relatively uncommon. As Table 2 shows, *mudaraba* and *musharaka* products are issued[19] by 17.2 percent of Islamic MFIs, and an average of 22.6 percent of Islamic MFI clients use these products.[20] This preference might reflect the high risk associated with equity products and the difficulties associated with determining a project's yield, which would imply the need for costly monitoring. Instead, debt instruments, and *murabaha* and *qard e hasan* in particular, are substantially more common than equity instruments. In Table 2, 75.8 percent of Islamic MFIs provide *murabaha*, 58.6 percent provide *qard e hasan*, and 20.7 percent provide *sala'm* products. On average, 47.6 percent of Islamic microfinance clients use *murabaha*, 23.1 percent use *qard e hasan*, and 18.2 percent use *sala'm*. Thus, our results establish that Islamic MFIs and their clients mainly rely on *murabaha* and *qard e hasan*.

Second, there are some notable similarities and differences between Islamic and conventional MFIs, in terms of their clientele, lending techniques, and funding sources. According to Table 3, both types attract a predominantly female client base, such that 64.4 percent of Islamic MFI and 63.6 percent of conventional MFI clients are female on average. On average, 17.2 percent of clients of conventional MFIs are employed as salaried workers, compared with 12.3 percent for Islamic MFIs, which aligns with the higher average percentage of poor members in Islamic MFIs' customer bases (45.2% versus 43.4%). Neither of these differences is statistically significant though. Other differences appear more substantial, such that 45.6 percent of Islamic MFIs' client bases engage in farming, versus only 34.2 percent for conventional MFIs (p = .031). In addition, 53.5 percent of conventional MFIs' customer base includes micro-entrepreneurs, compared with 40.9 percent for Islamic MFIs (p = .043). Table 3 reveals no statistically significant differences in terms of the MFIs' reliance on rural lending, group lending, or donor agencies, yet a significantly higher percentage of Islamic MFIs report government support (37 percent) and Zakat funds[21] (7.4 percent) as main sources of funding.

4.3. Regression results: outreach and financial sustainability

4.3.1. Data and descriptive statistics

Table 4 describes the variables used in the regression analyses in detail. In particular, for our outreach dependent variable, we include measures of both breadth (serving many people, even if they are somewhat less poor) and depth (serving the poorest segments of the population) (Brau & Woller, 2004; Schreiner, 2002). The measure of breadth of outreach uses the logarithm of the number of active borrowers (*LNNAB*) of MFI i operating in country j at time t (Cull, Demirgüç-Kunt, & Morduch, 2009; Louis et al., 2013; Mersland & Strøm, 2009); the measure of depth reflects the ratio of the average loan size of MFI i at time t to the gross national income per capita at time t (*ALBGNI*) of the country j in which it operates. Greater depth implies smaller values of *ALBGNI*. Although we note the ongoing discussion about the validity of the outreach measures (see Section 2.2), more appropriate indicators have not been established yet, so we maintain standard outreach indicators, in line with prior literature (Cull et al., 2007; Fan et al., 2019; Hermes et al., 2011; Mersland & Strøm, 2010; Quayes, 2012), even while acknowledging that they can only give an indication of the

[17] For each region, we calculate the average shares of current Islamic MFIs and of expected future Islamic MFIs. Then, the expected growth rate of the share of Islamic MFIs per region is calculated as (average share of future Islamic MFIs – average share of current Islamic MFIs)/average share of current Islamic MFIs.

[18] For more information, please see *contextual details* in Appendix A.1.1.

[19] We calculate the percentage of Islamic MFIs providing a certain Islamic financial product as (number of Islamic MFIs offering a particular Islamic product/total number of Islamic MFIs) × 100.

[20] We calculate the percentage of clients using Islamic products as (number of clients using the offered product/total number of clients) × 100 for each MFI that offers a particular product. The values in the text represent simple averages of this percentage, across all MFIs that offer the product.

[21] Zakat is a charitable contribution, mandatory for Muslims who seek to satisfy criteria related to their wealth.

Table 4
Variable definitions and sources.

Variable	Abbreviation	Definition
Main Variable of Interest		
Islamic microfinance institution	ISMFI	Dummy variable, 1 if the MFI uses Islamic lending techniques; 0 otherwise. Source: Survey.
Country-Specific Variables		
GDP growth	GDPgrowth	How fast the economy is growing, calculated by comparing one year of the country's GDP to the previous year. Source: http://data.worldbank.org
Instruments		
Percent of Muslim population	PMP	Percentage of Muslims residing in the country. Source: Kettani (2010)
Islamic state	Islstate	Dummy variable equal to 1 if the official state religion of the country is Islam and 0 otherwise. Source: Barro and McCleary (2005)
Dependent Variables		
Log of number of active borrowers	LNNAB	Log number of entities with currently outstanding loan balances with the MFI or that are primarily responsible for repaying any portion of the gross loan portfolio. Entities with multiple loans with an MFI are counted as a single borrower.
Average loan balance per borrower/GNI per capita	ALBGNI	Average deposit balance per depositor, relative to local GNI per capita, which provides an estimate of the coverage of the low-income population achieved through deposits. The indicator, calculated in national currencies, is converted to U.S. dollars at official exchange rates to enable comparisons across economies. To smooth fluctuations in prices and exchange rates, a special Atlas method of conversion is used, as suggested the World Bank.
Return on assets	ROA	Measure of how well an MFI manages its assets to optimize its profitability. This ratio is net of income taxes and excludes donations and non-operating items. It is calculated as net operating income (less taxes) relative to average assets.
MFI-Specific Variables		
Market share	Mktshare	Market concentration of an MFI in terms of earning revenue. We take the fraction of financial revenue earned by an MFI in a given year with respect to total financial revenues in a given year earned by all MFIs in the country.
Market size	Mktsize	Market size is proxied by the log of the assets, or the total value of resources controlled by MFI as a result of past events, from which future economic benefits are expected to flow. For the calculation, assets are the sum of each individual asset account listed.
Portfolio at risk >30 days	PAR	Portion of the loan portfolio "contaminated" by arrears and at risk of not being paid back. It represents the outstanding balance in arrears over 30 days in addition to restructured loans, divided by total outstanding gross portfolio.
Capital-to-assets ratio	CAR	Representing institutional solvency, it is calculated as total capital divided by risk-weighted assets.
Yield on gross loan portfolio	YGLP	Earning performance of an MFI, according to how effectively the MFI matches the maturities of its assets and liabilities. It is calculated as financial revenue from the loan portfolio, divided by average gross loan portfolio.
Gross loan portfolio-to-assets ratio	GLP/assets	The relation of an MFI's loan portfolio to total assets, calculated as gross loan portfolio divided by total assets.
Maturity in Age	DumAge	The length of duration since the MFI's establishment. The dummy variable equals to 1 if the age of an MFI is over 8 years and 0 otherwise.
Regulated	DumReg	Dummy variable equal to 1 if the MFI is regulated by some supervisory authority and 0 otherwise.

Notes: Unless otherwise noted, the source for these variables is MIX Market.

social performance of MFIs. We measure financial performance as the return on assets (*ROA*), or the ratio of net operating income to total assets (Ahlin, Lin, & Maio, 2011; Armendáriz & Morduch, 2010; Mersland & Strøm, 2009; Servin et al., 2012; Strøm et al., 2014),[22] which varies across MFIs and time.

Table 5 provides the means, standard deviations, and ranges of all the variables in our main regression, including the three dependent variables. Foreshadowing our regression analysis, we list these summary statistics separately for Islamic and conventional MFI subsamples (i.e., for which we compare the conditional means in our regression analysis). The log of the number of borrowers is similar across Islamic and conventional MFIs, suggesting a similar breadth of outreach. But the average loan balance per borrower (scaled by gross national income per capita) is much smaller for Islamic than for conventional MFIs (US$0.4 and 0.6, respectively), so the depth of outreach appears higher for Islamic MFIs. In terms of financial performance, Islamic MFIs underperform; their mean ROA value is lower, equal to −0.6 percent, compared with 0.9 percent for conventional MFIs. The purpose of our regression analysis is to explore these differences in a more robust manner.

The regression analysis also includes a vector of the following control variables: (1) market share, which reflects the market concentration of an MFI in terms of earning revenue (*Mktshare*); (2) market size proxied by the log of assets (*Mktsize*), which is MFI- and time-specific; (3) whether the portfolio at risk is greater than 30 days (*PAR*), which is MFI- and time-specific; (4) the capital-to-assets ratio (*CAR*), which is MFI- and time-specific; (5) the yield on the gross loan portfolio (*YGLP*); (6) the ratio of the gross loan portfolio to assets (GLP/assets); (7) age (*AgeDummy*) as a dummy variable, where 1 = mature MFI and 0 otherwise, which is MFI- and time-specific; and (8) the regulatory status of the MFI (*RegDummy*), another dummy variable, where 1 = MFI is regulated and 0 otherwise, which is MFI-specific. We also include a country- and time-specific control variable GDP growth (*GDPgrowth*) to capture general business cycle variation in the dependent variables in our panel models. This variable, when used in our cross-sectional specifications, controls for the average growth rate of a country in the sample period. Finally, we include time dummies in the panel regressions. As noted, the definitions, abbreviations, and sources of the variables used in our regression analyses are in Table 4. Then Table 5 shows that, with the exception of PAR (clearly higher for Islamic MFIs), the control variables are similar across the two groups of MFIs.

[22] In banking studies, it is common to use return on equity (ROE) to measure financial performance, but in microfinance studies, it is more common to use ROA, because ROE depends on the firm's capital structure and equity. Our sample includes non-profit MFIs, which lack equity capital for earnings purposes. As an advantage of ROA, it evokes the same interpretation in all categories of MFIs, which facilitates comparisons.

Table 5
Descriptive Statistics.

Variable	Full sample (response = 1)					Islamic MFIs					Conventional MFIs				
	Obs.	Mean	SD	Min.	Max.	Obs.	Mean	SD	Min.	Max.	Obs.	Mean	SD	Min.	Max.
Dependent Variables															
ALBGNI	5,045	0.61	1.27	0	30.67	491	0.43	0.47	0.01	3.35	4,554	0.63	1.33	0	30.67
LNNAB	5,086	9.47	1.90	2.49	15.92	499	9.55	1.92	4.58	14.06	4,587	9.46	1.90	2.49	15.92
ROA	4,407	0.01	0.13	−3.45	1.01	414	−0.01	0.15	−1.45	0.26	3,993	0.01	0.13	−3.45	1.01
Independent Variables															
GDPgrowth	5,365	4.98	3.39	−28.10	54.16	525	4.96	4.71	−28.10	54.16	4,840	4.98	3.21	−20.49	34.50
Mktshare	4,975	0.12	0.22	−0.48	2.15	490	0.17	0.27	−0.21	1	4,485	0.11	0.21	−0.48	2.15
Mktsize	5,209	15.87	2.01	5.43	22.69	512	15.76	1.76	9.49	19.95	4,697	15.88	2.03	5.43	22.69
PAR	5,330	0.05	0.12	0	5.48	522	0.08	0.27	0	5.48	4,808	0.05	0.09	0	1.05
CAR	5,188	0.34	0.31	−4.13	7.12	504	0.42	0.38	−1.87	1	4,684	0.33	0.31	−4.13	7.12
YGLP	5,312	0.24	0.25	−1.33	11.48	520	0.24	0.54	0	11.48	4,792	0.23	0.20	−1.33	1.52
GLP/assets	5,181	0.76	0.34	0	11.95	506	0.72	0.23	0	3.68	4,675	0.76	0.35	0	11.95
DumAge	5,366	0.69	0.46	0	1	526	0.60	0.49	0	1	4,840	0.70	0.46	0	1
DumReg	5,366	0.67	0.47	0	1	526	0.61	0.49	0	1	4,840	0.67	0.47	0	1
Instrumental Variables															
PMP	5,366	33.86	39.64	0.01	99.98	526	73.20	32.61	0.01	99.98	4,840	29.58	37.95	0.01	99.77
Islstate	5,366	0.21	0.41	0	1	526	0.68	0.47	0	1	4,840	0.16	0.36	0	1

Notes: This table lists summary statistics for key variables for the full sample of respondents, Islamic MFIs, and conventional MFIs. *Obs* is the number of observations for each variable; *SD* is standard deviation; and *Min* and *Max* are the minimum and maximum values for the variables, respectively.

Table 6
Regression results for outreach: ALBGNI.

Variables	Group Means	Fama MacBeth	Random Effects	Random Effects with IV	Inverse Probability with IV
ISMFI	−0.257*	−0.225***	−0.276***	−1.212***	−1.120***
	(0.132)	(0.030)	(0.103)	(0.431)	(0.329)
GDPgrowth	0.184	0.018	0.009**	0.010**	0.008
	(0.137)	(0.010)	(0.004)	(0.004)	(0.011)
Mktshare	1.757***	0.704***	−0.241**	−0.153	0.704***
	(0.667)	(0.080)	(0.120)	(0.111)	(0.253)
Mktsize	0.058	0.078***	0.084***	0.084***	0.049**
	(0.050)	(0.011)	(0.023)	(0.020)	(0.023)
PAR	0.029	0.594	−0.181	−0.172**	0.156**
	(0.872)	(0.413)	(0.115)	(0.081)	(0.077)
CAR	−0.319	−0.130***	0.075	0.066	−0.092
	(0.234)	(0.040)	(0.080)	(0.075)	(0.130)
YGLP	−0.001	−0.642***	−0.230***	−0.181*	−0.612***
	(0.635)	(0.114)	(0.079)	(0.094)	(0.191)
GLP/assets	−0.892*	−0.420***	0.028	0.017	−0.204*
	(0.467)	(0.112)	(0.048)	(0.036)	(0.110)
DumAge	−0.111	−0.151***	−0.009	−0.024	−0.188**
	(0.174)	(0.037)	(0.044)	(0.048)	(0.089)
DumReg	0.270***	0.298***	0.400***	0.383***	0.293***
	(0.104)	(0.040)	(0.144)	(0.144)	(0.070)
Constant	1.228	−0.400*	−0.742**	−0.656**	−0.457
	(5.352)	(0.215)	(0.314)	(0.278)	(0.385)
Time dummies	Yes	Yes	Yes	Yes	Yes
Observations	4,680	4,680	4,680	4,680	4,637
R-squared	0.177	0.137	0.037	0.029	0.035
Number of MFIID/ groups	571	18	571	571	563
Weak Identification Test					
F-statistic of excluded instruments				29.30***	13.49***
Stock-Yogo critical values (TSLS bias)				11.57	11.57
Stock-Yogo critical values (TSLS size)				11.59	11.59
Overidentification Test of All Instruments					
Hansen statistic				0.874	3.822
p-Value Hansen test				0.349	0.051

Notes: Standard errors for Group means and RE estimates are based on a bootstrapping method; for Random Effects with IV and Inverse Probability with IV, the standard errors are robust clustered standard errors (with MFI as the cluster). *Group means* refers to a between-subjects estimator (based on Group means); *Fama MacBeth* refers to results using the Fama-MacBeth method; *Random Effects* refers to a random effects panel estimate; *Random Effects with IV* refers to a random effects with instruments panel estimate; and *Inverse Probability with IV* refers to panel estimate that combines inverse probability weighting and instruments. The Stock-Yogo TSLS bias critical values are critical values for the weak instrument test based on TSLS bias (5% significance). The critical value is a function of the number of included endogenous regressors (in our case, 1), the number of instrumental variables (in our case, 2), and the desired maximal bias of the IV estimator relative to ordinary least squares (in our case, 1%). The critical value is obtained from Skeels and Windmeijer (2018); Stock and Yogo (2005) do not present relative bias tables for two instrumental variables. The Stock-Yogo TSLS size critical values are critical values for the weak instrument test based on TSLS size (5% significance). The critical value is a function of the number of included endogenous regressors (in our case, 1), the number of instrumental variables (in our case, 2), and the desired maximal size (in our case, 15%) of a 5 percent Wald test where $\beta = \beta 0$.
* Significant at 0.10%. ** Significant at 0.05%. *** Significant at 0.01%.

4.3.2. Regression results

We present the regression results in Table 6 (depth of outreach, dependent variable *AVLNGNI*), Table 7 (breadth of outreach, dependent variable *LNNAB*), and Table 8 (financial performance, dependent variable *ROA*). In each table, we provide results obtained with the five estimation methods we introduced previously (Group means, FM, RE, REIV, and IPWIV). Supplementary regressions for the first-stage are provided in Appendix C, Table C.1 and C2.

In Table 6, the coefficients for the Islamic MFI dummy variable are negative and highly statistically significant in all specifications. Therefore, and in line with our first hypothesis, Islamic MFIs appear to exhibit greater *depth* of outreach than conventional MFIs, controlling for macroeconomic growth, the size of the MFI proxied by the log of assets (*Mktsize*), the age of the MFI, other relevant MFI characteristics (e.g., market concentration), being regulated, and time dummies. Most of the regression models show that MFIs with greater market shares (Mktshare) and bigger, more regulated MFIs (*Mktsize* and *DumReg*, respectively) offer less depth of outreach. Somewhat surprisingly, older MFIs reveal greater depth. We also note some indications that periods of higher GDP growth are associated with less depth of outreach. Only the random-effects specifications RE and REIV show significant results. Finally, the coefficients for the portfolio at risk and capital-to-assets ratio are mostly statistically insignificant in Table 6.

The coefficients for the Islamic MFI dummy variable in Table 7 are positive and highly statistically significant across almost all regressions (cf. RE); Islamic MFIs exhibit greater *breadth* of outreach than conventional MFIs, *ceteris paribus*. Apparently, potential liquidity problems created because Islamic MFIs cannot borrow from conventional MFIs (see Section 2) do not restrict their breath of outreach. Larger MFIs, measured by asset size, also indicate greater breadth, which contrasts with the results for depth. But in line with our depth results, we find that older MFIs indicate greater breadth in most specifications. That is, older MFIs seem to have greater outreach, in terms of both depth and breadth. Regulated MFIs, according to most specifications, exhibit less breadth and depth. According to the coefficients on GDP growth in most specifications, countries that grew faster on average in the sample period also featured greater breadth of outreach. The portfolio at risk and capital-to-assets ratio coefficients suggest that higher values are associated with less breadth, though not always significantly.

The size of the coefficient for *ISMFI* is similar for the Group means, FM, and RE estimates, which offers some reassurance regarding the robustness of the results. However, the (absolute value of the) coefficient for ISMFI is bigger for both IV estimates (REIV and IPWIV). The relative magnitude of the estimates, and the ability of the IV estimates to correct for endogeneity bias,

Table 7
Regression Results for Outreach: LNNAB.

Variables	Group Means	Fama MacBeth	Random Effects	Random Effects with IV	Inverse Probability with IV
ISMFI	0.456***	0.356***	0.162	2.726***	3.059***
	(0.142)	(0.084)	(0.142)	(0.597)	(0.793)
GDPgrowth	0.128***	0.057***	−0.006*	−0.006*	0.055***
	(0.041)	(0.015)	(0.003)	(0.003)	(0.017)
Mktshare	−0.877**	−0.370***	0.391***	0.378***	−0.353
	(0.386)	(0.092)	(0.099)	(0.094)	(0.387)
Mktsize	0.746***	0.699***	0.747***	0.750***	0.821***
	(0.044)	(0.032)	(0.030)	(0.028)	(0.037)
PAR	−1.668**	−1.468***	−0.043	−0.044	−0.538**
	(0.703)	(0.250)	(0.112)	(0.097)	(0.209)
CAR	−0.371	−0.402***	−0.105	−0.108	−0.483**
	(0.246)	(0.061)	(0.083)	(0.077)	(0.240)
YGLP	0.085	0.548**	0.326***	0.302***	0.739**
	(0.522)	(0.213)	(0.092)	(0.104)	(0.296)
GLP/assets	0.619***	0.664***	0.445***	0.446***	0.593***
	(0.206)	(0.102)	(0.167)	(0.144)	(0.157)
DumAge	0.470***	0.449***	0.066	0.070*	0.348***
	(0.157)	(0.102)	(0.040)	(0.042)	(0.132)
DumReg	−0.206*	−0.059	−0.265**	−0.235*	−0.170
	(0.108)	(0.059)	(0.108)	(0.131)	(0.146)
Constant	4.725	−2.547***	−2.535***	−2.877***	−3.493***
	(5.217)	(0.488)	(0.404)	(0.384)	(0.586)
Time dummies	Yes	Yes	Yes	Yes	Yes
Observations	4,693	4,693	4,693	4,693	4,650
R-squared	0.629	0.619	0.588	0.769	0.517
Number of MFIID/ groups	571	18	571	571	563
Weak Identification Test					
F-statistic of excluded instruments				29.52***	13.59***
Stock-Yogo critical values (TSLS bias)				11.57	11.57
Stock-Yogo critical values (TSLS size)				11.59	11.59
Overidentification Test of All Instruments					
Hansen statistic				0.000	0.382
p-Value Hansen test				0.985	0.536

Notes: Standard errors for Group means and RE estimates are based on a bootstrapping method; for Random Effects with IV and Inverse Probability with IV, the standard errors are robust clustered standard errors (with MFI as the cluster). *Group means* refers to a between-subjects estimator (based on Group means); *Fama MacBeth* refers to results using the Fama-MacBeth method; *Random Effects* refers to a random effects panel estimate; *Random Effects with IV* refers to a random effects with instruments panel estimate; and *Inverse Probability with IV* refers to panel estimate that combines inverse probability weighting and instruments. The Stock-Yogo TSLS bias critical values are critical values for the weak instrument test based on TSLS bias (5% significance). The critical value is a function of the number of included endogenous regressors (in our case, 1), the number of instrumental variables (in our case, 2), and the desired maximal bias of the IV estimator relative to ordinary least squares (in our case, 1%). The critical value is obtained from Skeels and Windmeijer (2018), Stock and Yogo (2005) do not present relative bias tables for two instrumental variables. The Stock-Yogo TSLS size critical values are critical values for the weak instrument test based on TSLS size (5% significance). The critical value is a function of the number of included endogenous regressors (in our case, 1), the number of instrumental variables (in our case, 2), and the desired maximal size (in our case, 15%) of a 5 percent Wald test where $\beta = \beta 0$.
* Significant at 0.10%. ** Significant at 0.05%. *** Significant at 0.01%.

Table 8
Regression results for financial performance: ROA.

Variables	Group Means	Fama MacBeth	Random Effects	Random Effects with IV	Inverse Probability with IV
ISMFI	−0.013	−0.022*	−0.013	−0.066	−0.043
	(0.025)	(0.012)	(0.020)	(0.054)	(0.036)
GDPgrowth	−0.002	0.001	0.001	0.001	0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Mktshare	−0.005	0.001	−0.001	−0.003	−0.018
	(0.023)	(0.012)	(0.036)	(0.034)	(0.019)
Mktsize	0.015***	0.011***	0.027***	0.024***	0.010***
	(0.005)	(0.002)	(0.005)	(0.004)	(0.002)
PAR	−0.216	−0.161***	−0.064	−0.067*	−0.009
	(0.191)	(0.038)	(0.046)	(0.039)	(0.023)
CAR	0.097***	0.064***	0.065***	0.067***	0.088***
	(0.030)	(0.016)	(0.024)	(0.023)	(0.012)
YGLP	−0.061	−0.101	0.124***	0.104**	0.018
	(0.088)	(0.060)	(0.043)	(0.044)	(0.031)
GLP/assets	0.068***	0.090***	0.041***	0.040***	0.046***
	(0.025)	(0.018)	(0.011)	(0.011)	(0.008)
DumAge	0.001	0.032***	0.005	0.007	0.016*
	(0.028)	(0.008)	(0.007)	(0.007)	(0.008)
DumReg	0.018	0.010	0.011	0.012	0.012
	(0.014)	(0.012)	(0.015)	(0.015)	(0.008)
Constant	−0.188	−0.276***	−0.426***	−0.379***	−0.180***
	(0.276)	(0.057)	(0.084)	(0.061)	(0.059)
Time dummies	Yes	Yes	Yes	Yes	Yes
Observations	4,379	4,379	4,379	4,379	4,338
R-squared	0.142	0.215	0.065	0.092	0.083
Number of MFIID/ groups	563	18	563	563	556
Weak Identification Test					
F-statistic of excluded instruments				27.36***	12.47***
Stock-Yogo critical values (TSLS bias)				11.57	11.57
Stock-Yogo critical values (TSLS size)				11.59	11.59
Overidentification Test of All Instruments					
Hansen statistic				6.151	0.974
p-Value Hansen test				0.013	0.327

Notes: Standard errors for Group means and RE estimates are based on a bootstrapping method; for Random Effects with IV and Inverse Probability with IV, the standard errors are robust clustered standard errors (with MFI as the cluster). *Group means* refers to a between-subjects estimator (based on Group means); *Fama MacBeth* refers to results using the Fama-MacBeth method; *Random Effects* refers to a random effects panel estimate; *Random Effects with IV* refers to a random effects with instruments panel estimate; and *Inverse Probability with IV* refers to panel estimate that combines inverse probability weighting and instruments. The Stock-Yogo TSLS bias critical values are critical values for the weak instrument test based on TSLS bias (5% significance). The critical value is a function of the number of included endogenous regressors (in our case, 1), the number of instrumental variables (in our case, 2), and the desired maximal bias of the IV estimator relative to ordinary least squares (in our case, 1%). The critical value is obtained from Skeels and Windmeijer (2018); Stock and Yogo (2005) do not present relative bias tables for two instrumental variables. The Stock-Yogo TSLS size critical values are critical values for the weak instrument test based on TSLS size (5% significance). The critical value is a function of the number of included endogenous regressors (in our case, 1), the number of instrumental variables (in our case, 2), and the desired maximal size (in our case, 15%) of a 5 percent Wald test where $\beta = \beta 0$. * Significant at 0.10%. ** Significant at 0.05%. *** Significant at 0.01%.

may seem to suggest that the actual effect size is greater than implied by our OLS estimates, but this conclusion would be unwarranted. In the OLS regression, the independent variable ISMFI is binary (0, 1), but the IV procedure transforms it into a probability. Because the probability of being an ISMFI is always less than 1, the coefficient would need to be larger to produce the same effect size. Therefore, the IV estimates in our case, where the endogenous variable is a dummy, likely overestimate the actual effect size.[23]

Finally, Table 8 provides weak evidence in support of our second hypothesis that Islamic MFIs financially underperform conventional MFIs. The point estimate of the coefficient for IMFI is negative for all regressions but statistically insignificant in almost all cases. Apparently, the higher operational costs associated with debt-like contracts (e.g., *murabaha*) and the potential for adverse selection problems that arise when Islamic MFIs use PLS contracts do not lead to significantly lower ROA. However, more research is needed to explain the precise reasons for this outcome. Arguably, it could arise because Islamic MFIs receive funding from donations. In addition, in terms of control variables, larger MFIs and those with higher capital-to-assets ratio display significantly higher ROA.

In summary, the results in Tables 6 and 7 strongly suggest that outreach by Islamic MFIs is better than that by conventional MFIs, in terms of both depth and breadth, so we confirm our first hypothesis. However, Table 8 only provides weak evidence for our hypothesis that Islamic MFIs underperform financially: The coefficient is negative but almost always insignificant.

As we noted in the previous section, two approaches (REIV and IPWIV) use instruments to control for the possible endogeneity bias.[24] Valid (external) instruments must correlate with the endogenous variable (*ISMFI)* but not the error term. Thus, appropriate exclu-

[23] In an effort to make IV and OLS estimates comparable, de Jong (2016) suggests correcting the coefficient of the IV estimate by multiplying it by the mean value of the first-step regression fitted values. In our case, we could approximate this value by taking the percentage of Islamic MFIs in the data set (i.e., percentage of 1 values for the endogenous dummy). When we do so, recalling that the percentage of Islamic MFIs is about 11 percent, the coefficients of the IV estimates become comparable to those of the OLS estimates.

[24] Although the data for most of the control variables come from the Mix Market data set, information about two instruments (percentage of Muslim population and being an Islamic state) comes from other sources, which theoretically could introduce a bias.

sion restrictions need to hold, and the instruments cannot affect outcome variables unless they go through *ISMFI*. We use the Hansen J statistic tests for joint instrument validity to test the null hypothesis that the instruments are valid and uncorrelated with the error term. Lower *p*-values indicate stronger evidence that the instruments are not valid, so rejecting the null hypothesis of the validity of the instruments would need to be reconsidered. However, not rejecting the null hypothesis does not mean the instruments are valid. We also test for the failure of the relevance condition and weak instruments. The first-stage F-statistic of the excluded instrument is, in case of a single endogenous variable (as in our case), equal to the Kleinbergen-Paap F statistic; we compare it with Stock and Yogo (2005) critical values. According to the relevant IV test statistics in Tables 6–8, for all models, the null hypothesis of weak instruments is rejected, as also is true for small instrumental biases relative to the OLS estimator and small IV sizes. Moreover, the Hansen J statistic suggests that we cannot reject the null prediction of instrumental validity for all but two specifications (ALBGNI in inverse probability with IV and ROA in random effects with IV).

4.3.3. Robustness checks

In addition to the regression results in Tables 6–8, we present three sets of alternative regressions in Appendix D, see Table D1, D.2.1, D.2.2, D.2.3, D.3.1, D.3.2, D.3.3, D.4.1, D.4.2 and D.4.3. First, we consider a limited set of control variables, such that we exclude time dummies. Second, we include a control variable for fees and commission in another set of regressions, because Islamic MFIs might charge fees.[25] Controlling for fees in the estimates might be relevant, because excluding them could bias financial performance measures. Although we have limited information about these fees and thus cannot control fully for this potential bias, MixMarket publishes, for a limited group of MFIs, information about a variable it calls "Fee and commission income on loan portfolio," which includes "penalties, commissions, and other fees earned on the loan portfolio, other than penalty fees for late payment. It also includes revenues under Islamic finance methods." Therefore, we add this partial control (see Table D.1) and provide the regression results in Appendix D.[26] Third, another set of regressions (Tables D.4.1 to D.4.3) uses the binary dummy for Sharia-compliant MFIs as the main independent variable; it identifies Islamic MFIs that *only* offer Islamic microfinance products (whereas in the main analysis, we also included Islamic MFIs that offer both conventional and Islamic microfinance products). We thus can consider whether Islamic MFIs offering conventional products differ from those offering only Islamic products. In Appendix D, the three sets of additional regressions provide results very similar to our main regressions, in support of the robustness of our results.

5. Conclusion

This study has pursued two main aims. First, we sought a clearer picture of the global expansion and performance of Islamic MFIs by offering, to the best of our knowledge, the first comprehensive mapping of their global presence. Second, we attempt to provide a comparative analysis of their performance, relative to that of conventional MFIs.

The mapping exercise identifies 101 institutions in 33 countries offering Sharia-compliant microfinance services. South Asia accounts for the largest number of Islamic MFIs, with 30 (13 in Pakistan, 9 in Bangladesh). The Middle East and North Africa also feature many Islamic MFIs, with 29 providers, and sub-Saharan Africa accounts for 23 Islamic MFIs. In terms of the availability of different types of Islamic financial products, *murabaha*, a debt-based financing product, is the most widespread, and 64.7 percent of Islamic MFIs in our sample provide it. Due to the high risk associated with equity-based products such as *musharaka*, they are offered by relatively fewer MFIs.

When we test whether Islamic MFIs are better able to reach the socially oriented goal of increased outreach, in line with our predictions, we find that Islamic MFIs perform better. In particular, they serve more and poorer borrowers. In terms of financial results, we find some weak evidence that Islamic MFIs underperform conventional MFIs, though in most cases, the differences are not statistically significant.

Some caveats must be noted. The results clearly indicate that Islamic MFIs perform better in terms of outreach, but we reiterate the caution that we cannot address all the potential endogeneity issues. As a limitation of our analysis, we also cannot identify whether the positive results reflect differences in the production function between the two types of MFIs or differences in the clientele. In other words, we are not able to robustly identify whether the increase in outreach is due to *involuntary* or *voluntary* financial exclusion. Islamic clients, for religious reasons, may refuse to deal with conventional MFIs, so our results could be partly explained by demand effects and voluntary exclusion. Yet several studies assert that Muslim consumers are not solely interested in Islamic finance—Dar (2004) claims that that only 5 percent of U.K. Muslims seek Islamic financial services—so we reason that our results are more likely to be (mainly) explained by differences in production functions. Still, this conclusion requires caution, and our results should be interpreted as robust correlations rather than evidence of causality. We hope these findings in turn prompt continued comparative studies of the performance of Islamic and conventional MFIs along other dimensions, as well as studies that delve deeper into the reasons for their varying social performance.

CRediT authorship contribution statement

Syedah Ahmad: Conceptualization, Methodology, Formal analysis, Investigation, Writing - original draft, Data curation. **Robert Lensink:** Conceptualization, Methodology, Formal analysis, Investigation, Writing - original draft, Supervision. **Annika Mueller:** Conceptualization, Methodology, Investigation, Writing - original draft, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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[25] The service fee usually reflects the MFIs' administrative costs, incurred during loan disbursements. Generally, MFIs that provide *qard e hasan* (small, interest-free loans) charge less than 1 percent as a one-time fee (Maazullah, 2017). Although Islamic MFIs with equity-based contracts might charge higher fees, we lack detailed information about this feature in our data set.

[26] In addition, we have conducted estimates, for which, following Dorfleitner, Leidl, Priberny, and von Mosch (2013), we added a lending rate *LR* of MFIs calculated as;$LR = \frac{\text{Income}}{\text{GLP}*(1-\text{WOR})} + \frac{\text{Fees}}{\text{GLP}}$ where Income is interest/profit rate, Yield is yield on gross portfolio, GLP is gross loan portfolio, fees is fee and commission earned and *WOR* is the write-off ratio. The results are similar to the main results and can be obtained on request.

Appendix A. Data construction

A.1. Constructing the dataset

We construct our dataset by combining our online survey with the existing data sources and published reports. Below, we provide a detailed description of the data sources which are employed in our study.

A.1.2. Details for online survey

- *Survey format and implementation:* For receiving maximum responses we designed a short survey that can be completed within 5 min on average. For achieving this, we had to make a choice between amassing detailed information from Islamic microfinance institutions or gathering a more general information from both Islamic and non-Islamic microfinance institutions. To make the most use of a short survey, we collect information from both Islamic and non-Islamic microfinance institutions, about the indicators which are not available at MIX market database.

We organized our survey into three key sections: (1) identification of Islamic microfinance service providers; (2) provision of Islamic microfinance products; and (3) information about clientele, lending methodologies and sources of funding. We organized the questions in an order so that the information was first collected on the type of financial products offered i.e., interest-based, interest-free or both types. Following the response, we then asked specific questions each related to adherence with the Islamic principles or future plans of providing Islamic financial products.

With responses to Section 1, we identify those MFIs who at present provide microfinance products in line with Islamic principles as well as those MFIs who plan to provide such products in the future. Additionally, we identify those non-Islamic MFIs that are providing interest-free microfinance products. Section 2 was answered by Islamic MFIs only because we used skip and display logic in our survey design. Subject to the completion of the survey, Section 3 was filled by all responding MFIs.

- *Data collection mode:* We administered our online survey through Qualtrics; a web service used for conducting online surveys. We programmed Qualtrics to display one survey question at a time allowing the direct entry of the responses, while employing the display and skip logic checks. It also facilitates a user friendly survey design so that the survey can be accessed via mobile phone by the respondent. For quality controls and to avoid multiple responses by the same respondent, the system assigns only one specified web-link to each respondent email ID for survey participation. After the survey completion, the data can be downloaded from the server in a format compatible for analysis.
- *Contextual details:* Following details are for the calendar year 2016 that is the period when the online survey identifying Islamic MFIs is conducted. In our data, most of the Islamic MFIs are found to be not-profit MFIs. Concerning the market size in our data, total assets for non-profit Islamic MFIs are 1337 Million and for profit Islamic MFIs are149 Million. In terms of Active Borrowers, the end of the year 2016 shows non-profit Islamic MFIs to be the largest provider with over 4 Million clients and a market share of 296 Million. The share of non-profit Islamic microfinance segment remained stagnant at 3 Million in terms of number of depositors from 2015 to 2016. A quick highlight is provided in Table A.1.1 below.

Table A.1.1
Highlights of non-profit versus for-profit Islamic MFIs.

Variables	Non-Profit Islamic MFIs (in Millions)	For-Profit Islamic MFIs (in Millions)
Market size	1337	149
Market share	296	26
Gross Loan portfolio	1113	82
Number of borrowers	4	0.085
Number of depositors	3	0.285

Notes: The table represents the data for Islamic MFIs in 2016 and the values are presented in Million. Total assets are taken for representing market size; financial revenue is taken for representing market share. *Data source:* Author's survey and MIX market data.

A.1.2. Existing databases

MIX Market database: For MFI-level variables, we use the data (financial and social indicators) on the MFIs, provided by MIX Market.

World Bank: For country-level variables, we collected data from World Bank database and it includes information about country's growth.

A.1.3. Published reports

We consulted some published reports for constructing our instrumental variables, Kettani (2010) and Barro and McCleary (2005).

Appendix B. Variable's information/details

B.1. Percentage of Muslim population (PMP)

We use the data from Kettani (2010) because this is the only reference available that provides data covering the entire period of our study. Kettani provides the percentage of Muslims' population by using official census and reliable national sources of data.

The only other available dataset is the Pew Research Center dataset (2015) which is based on the data from the study conducted in 2009–2010. This source provides data for the last period (i.e., 2010 and 2020), but not for earlier period of our study. In order to avoid using two datasets for the same variable we preferred using the Kettani dataset for the entire period.[27]

Both available datasets use official census as the primary source for attaining percentage of Muslims which, for any country the official population census, is after every ten years. Thus, both of the available datasets have a time lapse of ten years. There is another caveat about Pew's report that it does not provide information about the growth rate of Muslims making it impossible for achieving the yearly percentage of the Muslim population. While Kettani documents annual population growth rate (APGR) which we employ to estimate the yearly percent of Muslims.

Since our study period is 1999–2016, we project the estimate for each year as $Population_{Future} = Population_{Present} x(1+i)^n$, where i is the growth rate and n is the number of years, which is 10 years for our study.

[27] We also compared the projections provided in the Kettani dataset with that of Pew Research Center dataset for 2010 and 2020. The correlation between the two datasets was extremely high (correlation coefficient is 0.998), so we don't have any reason to believe that the use of the Kettani dataset would bias our results.

Appendix C. Supplementary tables for first stage regressions.

Table C.1
Average Loan Balance per borrower per GNI (Instrumental random effects).

ISMFI	Coeff.	Robust Std. Err.	t	P > t
GDPgrowth	−0.0002	0.0001	−1.3	0.194
Mkrshare	0.014	0.005	2.59	0.010
Mktsize	−0.001	0.002	−0.69	0.491
PAR	0.003	0.002	1.22	0.224
CAR	0.003	0.004	0.8	0.424
YGLP	0.015	0.012	1.25	0.213
GLP/assets	0.000	0.001	−0.01	0.992
DumAge	−0.003	0.002	−2.08	0.037
DumReg	0.010	0.027	0.35	0.723
PMP	0.001	0.001	1.68	0.094
Islstate	0.238	0.062	3.86	0.000
Constant	0.028	0.026	1.07	0.285
Year Dummies	Yes			
Observations	4,680			

Notes: This table presents first stage results for instrumental random effects, where *Coeff* represents coefficient estimates, *Std. Err* shows the standard error term, and *t* represents t-statistics. *ISMFI* (a dummy variable which is 1 when an MFI provides Islamic financial products/services and 0 when it provides conventional financial products whether or not it charges interest rate from the clients) is the dependent variable for the first stage. *GDPgrowth* measures how fast the economy is growing and is calculated by comparing one year of the country's GDP to the previous year. *Mktshare* is the fraction of financial revenue earned by an MFI in a given year with respect to total financial revenues in a given year earned by all MFIs in the country. *Mktsize* is the log of total assets. *PAR* is portfolio at risk and is that portion of loan portfolio which is "contaminated" by arrears and is at the risk of not being paid back to MFI. *CAR* is capital to assets ratio representing the institutional solvency and is calculated as total capital divided by risk weighted assets. *YGLP* represents financial revenue from loan portfolio divided by average gross loan portfolio. *GLP/assets* measure the relation of an MFI's loan portfolio to the total assets. *DumAge* is a dummy variable that equals to 1 if the age of an MFI is over 8 years; 0 otherwise. *DumReg* is a dummy variable identifying an MFI as 1 if it is regulated by some supervisory authority; 0 otherwise. *PMP* is the percent of Muslim population in a country where MFI is located. *Islstate* is 1 if the state religion of the country is Islam; 0 otherwise.

C.2. Weighted instrumental regressions

C.2.1. Logistic regression for weighting the variables (inverse probability weighting)

Response	Coeff.	Std. Err.	z	P>z	[95% Conf.	Interval]
Fiscal Year						
2000	0.023	0.253	0.090	0.928	−0.473	0.519
2001	−0.055	0.237	−0.230	0.817	−0.520	0.410
2002	−0.224	0.226	−0.990	0.320	−0.667	0.218
2003	−0.416	0.220	−1.900	0.058	−0.847	0.014
2004	−0.389	0.217	−1.790	0.074	−0.815	0.037
2005	−0.418	0.216	−1.940	0.053	−0.841	0.005
2006	−0.417	0.216	−1.930	0.054	−0.841	0.007

C.2.1 (*continued*)

Response	Coeff.	Std. Err.	z	P>z	[95% Conf.	Interval]
2007	−0.418	0.218	−1.920	0.055	−0.844	0.009
2008	−0.428	0.218	−1.960	0.050	−0.855	−0.001
2009	−0.373	0.218	−1.710	0.087	−0.800	0.054
2010	−0.350	0.218	−1.610	0.108	−0.777	0.077
2011	−0.314	0.218	−1.440	0.150	−0.741	0.113
2012	−0.269	0.220	−1.220	0.221	−0.700	0.162
2013	−0.234	0.221	−1.060	0.290	−0.667	0.200
2014	−0.166	0.220	−0.750	0.450	−0.597	0.265
2015	−0.216	0.222	−0.970	0.330	−0.650	0.218
2016	−0.145	0.225	−0.640	0.521	−0.587	0.297
Legal status of MFIs						
CU	0.264	0.098	2.690	0.007	0.071	0.456
NBFI	0.288	0.081	3.540	0.000	0.128	0.447
NGO	0.791	0.094	8.420	0.000	0.607	0.975
Other	0.610	0.190	3.220	0.001	0.238	0.981
Rural Bank	−0.579	0.152	−3.820	0.000	−0.876	−0.282
GDPgrowth	0.0004	0.007	0.060	0.955	−0.014	0.015
Mktshare	0.759	0.148	5.140	0.000	0.470	1.049
Mktsize	0.093	0.014	6.520	0.000	0.065	0.122
PAR	−0.399	0.193	−2.070	0.038	−0.777	−0.022
CAR	0.119	0.071	1.690	0.092	−0.019	0.258
YGLP	0.855	0.115	7.440	0.000	0.630	1.080
GLP/assets	−0.015	0.012	−1.250	0.211	−0.039	0.009
DumAge	0.014	0.050	0.270	0.786	−0.084	0.111
DumReg	0.439	0.059	7.450	0.000	0.323	0.554
Constant	−2.755	0.362	−7.600	0.000	−3.465	−2.045
Observations	15,531					
Log likelihood	3180.13					
Pseudo R^2	0.165					

Notes: The dependent variable is a dummy, equal to 1 if the MFI returned the questionnaire. *Coeff* represents coefficient estimates, *Std. Err* shows the standard error term, and *z* represents z-statistics. As independent variables, we use dummies for the fiscal year. Legal status of the MFIs include; *Bank* is dummy variable identifying an MFI as 1 if statuary status is bank; 0 otherwise, *CU* is credit union/cooperative and is a dummy variable identifying an MFI as 1 if statuary status is a credit union or a cooperative; 0 otherwise, *NBFI* is Non-Banking Financial Intermediary and dummy variable identifying an MFI as 1 if statuary status is a credit union or a cooperative; 0 otherwise, *NGO* is non-governmental organization and is a dummy variable identifying an MFI as 1 if statuary status is non-governmental organization; 0 otherwise and *Other* is a dummy variable identifying an MFI as 1 if statuary status is other; 0 otherwise. *GDPgrowth* measures how fast the economy is growing and is calculated by comparing one year of the country's GDP to the previous year. *Mktshare* is the fraction of financial revenue earned by an MFI in a given year with respect to total financial revenues in a given year earned by all MFIs in the country. *Mktsize* is the log of total assets. *PAR* is portfolio at risk and is that portion of loan portfolio which is "contaminated" by arrears and is at the risk of not being paid back to MFI. *CAR* is capital to assets ratio representing the institutional solvency and is calculated as total capital divided by risk weighted assets. *YGLP* represents financial revenue from loan portfolio divided by average gross loan portfolio. *GLP/assets* measure the relation of an MFI's loan portfolio to the total assets. *DumAge* is a dummy variable that equals to 1 if the age of an MFI is over 8 years; 0 otherwise. *DumReg* is a dummy variable identifying an MFI as 1 if it is regulated by some supervisory authority; 0 otherwise.

Table C2
Average Loan Balance per GNI (Inverse Probability with Instrumental variables).

ISMFI	Coeff.	Robust Std. Err.	t	P > t
GDPgrowth	−0.0004	0.002	−0.180	0.860
Mkrshare	0.101	0.058	1.730	0.083
Mktsize	−0.009	0.006	−1.410	0.158
PAR	0.138	0.027	5.080	0.000
CAR	0.000	0.032	0.000	0.999
YGLP	−0.001	0.044	−0.020	0.986
GLP/assets	−0.010	0.009	−1.130	0.260
DumAge	−0.042	0.017	−2.400	0.017
DumReg	0.004	0.028	0.150	0.879
PMP	0.0001	0.0004	0.280	0.781
Islstate	0.312	0.067	4.680	0.000
Constant	0.116	0.098	1.190	0.236
Year Dummies	Yes			
Observations	4,637			

Notes: This table presents first stage results for instrumental random effects, where *Coeff* represents coefficient estimates, *Std. Err* shows the standard error term, and *t* represents t-statistics. *ISMFI* (a dummy variable which is 1 when an MFI provides Islamic financial products/services and 0 when it provides conventional financial products whether or not it charges interest rate from the clients) is the dependent variable for the first stage. *GDPgrowth* measures how fast the economy is growing and is calculated by comparing one year of the country's GDP to the previous year. *Mktshare* is the fraction of financial revenue earned by an MFI in a given year with respect to total financial revenues in a given year earned by all MFIs in the country. *Mktsize* is the log of total assets. *PAR* is portfolio at risk and is that portion of loan portfolio which is "contaminated" by arrears and is at the risk of not being paid back to MFI. *CAR* is capital to assets ratio representing the institutional solvency and is calculated as total capital divided by risk weighted assets. *YGLP* represents financial revenue from loan portfolio divided by average gross loan portfolio. *GLP/assets* measure the relation of an MFI's loan portfolio to the total assets. *DumAge* is a dummy variable that equals to 1 if the age of an MFI is over 8 years; 0 otherwise. *DumReg* is a dummy variable identifying an MFI as 1 if it is regulated by some supervisory authority; 0 otherwise. *PMP* is the percent of Muslim population in a country where MFI is located. *Islstate* is 1 if the state religion of the country is Islam; 0 otherwise.

Appendix D. Robustness checks.

Table D1
Variable definitions and descriptive statistics.

Variable name	Definition	N	Mean	SD
Fees and commission earned (Fees)	Fees and commission earned by an MFI refers to penalties, commissions, and other fees earned on the loan portfolio, excluding penalty fees for late payment. Under Islamic finance methods, this may also include revenues earned by an MFI.	3,519	7,82,187	3,008,610
Sharia compliant	Sharia compliant is a binary variable and indicates Islamic MFIs that *only* offer Islamic microfinance products.	5,366	0.041	0.198

Notes: This table reports variable definitions, number of observations (N), means and standard deviations (Std. Dev.) of the dependent variables used for data quality estimates. For fees, the data is taken from MIX Market and Sharia compliant stems from the authors' survey.

D.2. Results with smaller set of controls

Table D.2.1
Regression results for outreach: ALBGNI.

Variables	Group Means	Fama MacBeth	Random Effects	Random Effects with IV	Inverse Probability with IV
ISMFI	−0.317***	−0.150***	−0.333***	−1.226***	−0.949***
	(0.108)	(0.034)	(0.107)	(0.416)	(0.306)
GDPgrowth	0.130	0.014	0.009***	0.010***	0.010
	(0.130)	(0.009)	(0.003)	(0.004)	(0.010)
Mktsize	0.167***	0.112***	0.043**	0.049**	0.078***
	(0.065)	(0.011)	(0.021)	(0.020)	(0.022)
PAR	0.979	0.811	−0.179*	−0.169**	0.144
	(0.733)	(0.479)	(0.100)	(0.079)	(0.099)
CAR	−0.331*	−0.087***	0.072	0.066	−0.055
	(0.198)	(0.026)	(0.074)	(0.066)	(0.116)
DumAge	−0.379*	−0.190***	−0.050	−0.068	−0.193**
	(0.204)	(0.045)	(0.043)	(0.045)	(0.089)
DumReg	0.301*	0.309***	0.424***	0.406***	0.335***
	(0.179)	(0.035)	(0.156)	(0.139)	(0.071)
Constant	−2.368*	−1.297***	−0.193	−0.176	−0.692**
	(1.318)	(0.175)	(0.317)	(0.285)	(0.335)

Table D.2.1 (*continued*)

Variables	Group Means	Fama MacBeth	Random Effects	Random Effects with IV	Inverse Probability with IV
Observations	4,894	4,894	4,894	4,894	4,848
R-squared	0.064	0.095	0.036	0.018	0.022
Number of MFIID/ groups	584	18	584	584	576
Weak identification test					
F-statistic of excluded instruments				30.29***	13.58***
Stock-Yogo critical values (TSLS Bias)				11.57	11.57
Stock-Yogo critical values (TSLS Size)				11.59	11.59
Overidentification test of all instruments					
Hansen Statistic				0.683	5.204
P-value Hansen test				0.409	0.023

Notes: * refers to significant at 0.10%; ** significant at 0.05%; *** significant at 0.01%. Standard errors for Group Means and RE estimates are based on a bootstrapping method; For Random Effects with IV and Inverse Probability with IV standard errors are robust clustered standard errors (with MFI as cluster). *Group Means* refers to a between estimator (results based on group means); *Fama MacBeth* refers to results using the Fama MacBeth method; *Random Effects* refers to a random effects panel estimate; *Random Effects with IV* refers to a random effects with instruments panel estimate and *Inverse Probability with IV* refers to panel estimate that combines inverse probability weighting and instruments. The Stock-Yogo TSLS Bias critical values are critical values for the Weak Instrument Test Based on TSLS Bias: Significance level is 5%; The critical value is a function of the number of included endogenous regressors (in our case 1), the number of instrumental variables (in our case 2), and the desired maximal bias of the IV estimator relative to OLS (in our case 1%). The critical value is obtained from Skeels and Windmeijer (2018) as Stock-Yogo do not present relative bias tables for 2 instrumental variables (it present bias tables only for 3 or more instrumental variables).The Stock-Yogo TSLS Size critical values are critical values for the Weak Instrument Test Based on TSLS Size: Significance level is 5%; The critical value is a function of the number of included endogenous regressors (in our case 1), the number of instrumental variables (in our case 2), and the desired maximal size (in our case 15%) of a 5% Wald test of $\beta = \beta0$.

Table D.2.2
Regression results for outreach: LNNAB

Variables	Group Means	Fama MacBeth	Random Effects	Random Effects with IV	Inverse Probability with IV
ISMFI	0.357**	0.280***	0.144	2.454***	2.883***
	(0.142)	(0.079)	(0.159)	(0.566)	(0.790)
GDPgrowth	0.154***	0.066***	−0.001	−0.001	0.054***
	(0.036)	(0.014)	(0.003)	(0.003)	(0.015)
Mktsize	0.704***	0.681***	0.689***	0.688***	0.766***
	(0.037)	(0.029)	(0.021)	(0.021)	(0.033)
PAR	−1.892***	−1.604***	−0.076	−0.077	−0.537**
	(0.598)	(0.303)	(0.141)	(0.115)	(0.258)
CAR	−0.359*	−0.442***	−0.059	−0.060	−0.334
	(0.198)	(0.076)	(0.099)	(0.105)	(0.232)
DumAge	0.751***	0.477***	0.056	0.058	0.320**
	(0.141)	(0.104)	(0.047)	(0.045)	(0.130)
DumReg	−0.218**	−0.104*	−0.227**	−0.201	−0.160
	(0.104)	(0.050)	(0.098)	(0.123)	(0.147)
Constant	−2.769***	−1.628***	−1.508***	−1.779***	−3.288***
	(0.593)	(0.436)	(0.325)	(0.319)	(0.531)
Observations	4,914	4,914	4,914	4,914	4,868
R-squared	0.607	0.606	0.588	0.472	0.504
Number of MFIID/ groups	585	18	585	585	577
Weak identification test					
F-statistic of excluded instruments				30.48***	13.68***
Stock-Yogo critical values (TSLS Bias)				11.57	11.57
Stock-Yogo critical values (TSLS Size)				11.59	11.59
Overidentification test of all instruments					
Hansen Statistic				0.421	0.957
P-value Hansen test				0.516	0.328

Notes: * refers to significant at 0.10%; ** significant at 0.05%; *** significant at 0.01%. Standard errors for Group Means and RE estimates are based on a bootstrapping method; For Random Effects with IV and Inverse Probability with IV standard errors are robust clustered standard errors (with MFI as cluster). *Group Means* refers to a between estimator (results based on group means); *Fama MacBeth* refers to results using the Fama MacBeth method; *Random Effects* refers to a random effects panel estimate; *Random Effects with IV* refers to a random effects with instruments panel estimate and *Inverse Probability with IV* refers to panel estimate that combines inverse probability weighting and instruments. The Stock-Yogo TSLS Bias critical values are critical values for the Weak Instrument Test Based on TSLS Bias: Significance level is 5%; The critical value is a function of the number of included endogenous regressors (in our case 1), the number of instrumental variables (in our case 2), and the desired maximal bias of the IV estimator relative to OLS (in our case 1%). The critical value is obtained from Skeels and Windmeijer (2018) as Stock-Yogo do not present relative bias tables for 2 instrumental variables (it present bias tables only for 3 or more instrumental variables).The Stock-Yogo TSLS Size critical values are critical values for the Weak Instrument Test Based on TSLS Size: Significance level is 5%; The critical value is a function of the number of included endogenous regressors (in our case 1), the number of instrumental variables (in our case 2), and the desired maximal size (in our case 15%) of a 5% Wald test of β = β0.

Table D.2.3
Regression results for Financial Performance: ROA.

Variables	Group Means	Fama MacBeth	Random Effects	Random Effects with IV	Inverse Probability with IV
ISMFI	−0.016	−0.027**	−0.021	−0.092*	−0.054
	(0.024)	(0.012)	(0.021)	(0.054)	(0.038)
GDPgrowth	0.002	0.002*	0.001	0.001	0.002*
	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
Mktsize	0.011***	0.011***	0.018***	0.018***	0.008***
	(0.004)	(0.002)	(0.003)	(0.003)	(0.002)
PAR	−0.254	−0.152***	−0.074	−0.075*	−0.014
	(0.171)	(0.033)	(0.052)	(0.043)	(0.025)
CAR	0.086***	0.063***	0.077***	0.078***	0.092***
	(0.030)	(0.016)	(0.020)	(0.020)	(0.011)
DumAge	0.026	0.029***	0.001	0.003	0.015**
	(0.019)	(0.006)	(0.008)	(0.007)	(0.007)
DumReg	0.025*	0.005	0.015	0.014	0.011
	(0.015)	(0.014)	(0.015)	(0.015)	(0.009)
Constant	−0.237***	−0.200***	−0.325***	−0.305***	−0.165***
	(0.073)	(0.052)	(0.055)	(0.053)	(0.040)
Observations	4,390	4,390	4,390	4,390	4,349
R-squared	0.077	0.163	0.061	0.049	0.050
Number of MFIID/ groups	563	18	563	563	556
Weak identification test					
F-statistic of excluded instruments				27.57***	12.45***
Stock-Yogo critical values (TSLS Bias)				11.57	11.57
Stock-Yogo critical values (TSLS Size)				11.59	11.59
Overidentification test of all instruments					
Hansen Statistic				2.684	0.326
P-value Hansen test				0.101	0.568

Notes: * refers to significant at 0.10%; ** significant at 0.05%; *** significant at 0.01%. Standard errors for Group Means and RE estimates are based on a bootstrapping method; For Random Effects with IV and Inverse Probability with IV standard errors are robust clustered standard errors (with MFI as cluster). *Group Means* refers to a between estimator (results based on group means); *Fama MacBeth* refers to results using the Fama MacBeth method; *Random Effects* refers to a random effects panel estimate; *Random Effects with IV* refers to a random effects with instruments panel estimate and *Inverse Probability with IV* refers to panel estimate that combines inverse probability weighting and instruments. The Stock-Yogo TSLS Bias critical values are critical values for the Weak Instrument Test Based on TSLS Bias: Significance level is 5%; The critical value is a function of the number of included endogenous regressors (in our case 1), the number of instrumental variables (in our case 2), and the desired maximal bias of the IV estimator relative to OLS (in our case 1%). The critical value is obtained from Skeels and Windmeijer (2018) as Stock-Yogo do not present relative bias tables for 2 instrumental variables (it present bias tables only for 3 or more instrumental variables).The Stock-Yogo TSLS Size critical values are critical values for the Weak Instrument Test Based on TSLS Size: Significance level is 5%; The critical value is a function of the number of included endogenous regressors (in our case 1), the number of instrumental variables (in our case 2), and the desired maximal size (in our case 15%) of a 5% Wald test of β = β0.

D.3. Results after adding fees and commission on loans

Table D.3.1
Regression results for outreach: ALBGNI

Variables	Group means	Fama MacBeth	Random Effects	Random Effects with IV	Inverse Probability with IV
ISMFI	−0.242**	−0.217***	−0.176**	−1.024***	−1.056***
	(0.117)	(0.026)	(0.079)	(0.294)	(0.315)
GDPgrowth	0.027	0.018	0.005	0.005	0.003
	(0.024)	(0.012)	(0.004)	(0.004)	(0.008)
Fees	0.000	−0.000*	0.000	0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mktshare	1.566**	0.769***	−0.164	−0.056	0.950***
	(0.628)	(0.120)	(0.163)	(0.175)	(0.316)
Mktsize	0.034	0.081***	0.104***	0.099***	0.058**
	(0.043)	(0.009)	(0.023)	(0.020)	(0.025)
PAR	0.439	0.223*	−0.432***	−0.399***	0.280
	(0.823)	(0.118)	(0.128)	(0.121)	(0.199)
CAR	−0.366*	−0.080	0.061	0.052	−0.035
	(0.219)	(0.048)	(0.073)	(0.060)	(0.129)
YGLP	−0.084	−0.536***	−0.144	−0.099	−0.443**
	(0.540)	(0.143)	(0.111)	(0.101)	(0.180)
GLP/assets	−0.296	−0.300**	−0.004	−0.013	−0.274**
	(0.247)	(0.111)	(0.068)	(0.053)	(0.111)
DumAge	−0.109	−0.151***	−0.056	−0.074	−0.236***
	(0.138)	(0.041)	(0.052)	(0.056)	(0.085)
DumReg	0.156	0.197***	0.205	0.197	0.231***
	(0.128)	(0.032)	(0.146)	(0.134)	(0.072)
Constant	0.092	−0.480*	−1.119***	−0.945***	0.062
	(0.807)	(0.232)	(0.341)	(0.303)	(0.421)
Time dummies	Yes	Yes	Yes	Yes	Yes
Observations	3,348	3,348	3,348	3,348	3,324
R-squared	0.197	0.153	0.052	0.027	0.067
Number of MFIID/ groups	522	14	522	522	516
Weak identification test					
F-statistic of excluded instruments				28.68***	13.84***
Stock-Yogo critical values (TSLS Bias)				11.57	11.57
Stock-Yogo critical values (TSLS Size)				11.59	11.59
Overidentification test of all instruments					
Hansen Statistic				5.663	5.079
P-value Hansen test				0.017	0.024

Notes: * refers to significant at 0.10%; ** significant at 0.05%; *** significant at 0.01%. Standard errors for Group means and RE estimates are based on a bootstrapping method; For Random Effects with IV and Inverse Probability with IV standard errors are robust clustered standard errors (with MFI as cluster). *Group means* refers to a between estimator (results based on Group means); *Fama MacBeth* refers to results using the Fama MacBeth method; *Random Effects* refers to a random effects panel estimate; *Random Effects with IV* refers to a random effects with instruments panel estimate and *Inverse Probability with IV* refers to panel estimate that combines inverse probability weighting and instruments. The Stock-Yogo TSLS Bias critical values are critical values for the Weak Instrument Test Based on TSLS Bias: Significance level is 5%; The critical value is a function of the number of included endogenous regressors (in our case 1), the number of instrumental variables (in our case 2), and the desired maximal bias of the IV estimator relative to OLS (in our case 1%). The critical value is obtained from Skeels and Windmeijer (2018) as Stock-Yogo do not present relative bias tables for 2 instrumental variables (it present bias tables only for 3 or more instrumental variables).The Stock-Yogo TSLS Size critical values are critical values for the Weak Instrument Test Based on TSLS Size: Significance level is 5%; The critical value is a function of the number of included endogenous regressors (in our case 1), the number of instrumental variables (in our case 2), and the desired maximal size (in our case 15%) of a 5% Wald test of $\beta = \beta 0$.

Table D.3.2
Regression results for outreach: LNNAB

Variables	Group means	Fama MacBeth	Random Effects	Random Effects with IV	Inverse Probability with IV
ISMFI	0.317**	0.423***	0.095	2.300***	3.025***
	(0.162)	(0.066)	(0.165)	(0.522)	(0.745)
GDPgrowth	0.163***	0.064***	−0.008**	−0.008**	0.067***
	(0.031)	(0.019)	(0.003)	(0.003)	(0.019)
Fees	−0.000	−0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mktshare	−0.592	−0.456***	0.351***	0.334***	−0.587
	(0.423)	(0.123)	(0.111)	(0.097)	(0.443)
Mktsize	0.826***	0.762***	0.731***	0.732***	0.859***
	(0.047)	(0.021)	(0.028)	(0.029)	(0.047)
PAR	−1.183*	−1.249***	0.026	0.026	−0.743*
	(0.693)	(0.212)	(0.149)	(0.148)	(0.447)
CAR	−0.192	−0.520***	−0.134	−0.136*	−0.449*
	(0.296)	(0.077)	(0.088)	(0.079)	(0.266)
YGLP	0.223	0.848***	0.298**	0.271**	0.830**
	(0.582)	(0.177)	(0.128)	(0.133)	(0.365)
GLP/assets	0.469**	0.400**	0.598***	0.599***	0.843***
	(0.237)	(0.139)	(0.116)	(0.088)	(0.135)
DumAge	0.453***	0.235***	0.055	0.061	0.319**
	(0.141)	(0.073)	(0.043)	(0.042)	(0.155)
DumReg	−0.270**	−0.119***	−0.188*	−0.156	−0.121
	(0.108)	(0.026)	(0.101)	(0.127)	(0.154)
Constant	−4.762***	−3.341***	−2.793***	−3.085***	−5.925***
	(0.946)	(0.400)	(0.484)	(0.483)	(0.839)
Time dummies	Yes	Yes	Yes	Yes	Yes
Observations	3,355	3,355	3,355	3,355	3,331
R-squared	0.668	0.630	0.590	0.754	0.515
Number of MFIID/ groups	522	14	522	522	516
Weak identification test					
F-statistic of excluded instruments				29.27***	13.93***
Stock-Yogo critical values (TSLS Bias)				11.57	11.57
Stock-Yogo critical values (TSLS Size)				11.59	11.59
Overidentification test of all instruments					
Hansen Statistic				0.027	0.605
P-value Hansen test				0.869	0.437

Notes: * refers to significant at 0.10%; ** significant at 0.05%; *** significant at 0.01%. Standard errors for Group means and RE estimates are based on a bootstrapping method; For Random Effects with IV and Inverse Probability with IV standard errors are robust clustered standard errors (with MFI as cluster). *Group means* refers to a between estimator (results based on Group means); *Fama MacBeth* refers to results using the Fama MacBeth method; *Random Effects* refers to a random effects panel estimate; *Random Effects with IV* refers to a random effects with instruments panel estimate and *Inverse Probability with IV* refers to panel estimate that combines inverse probability weighting and instruments. The Stock-Yogo TSLS Bias critical values are critical values for the Weak Instrument Test Based on TSLS Bias: Significance level is 5%; The critical value is a function of the number of included endogenous regressors (in our case 1), the number of instrumental variables (in our case 2), and the desired maximal bias of the IV estimator relative to OLS (in our case 1%). The critical value is obtained from Skeels and Windmeijer (2018) as Stock-Yogo do not present relative bias tables for 2 instrumental variables (it present bias tables only for 3 or more instrumental variables).The Stock-Yogo TSLS Size critical values are critical values for the Weak Instrument Test Based on TSLS Size: Significance level is 5%; The critical value is a function of the number of included endogenous regressors (in our case 1), the number of instrumental variables (in our case 2), and the desired maximal size (in our case 15%) of a 5% Wald test of $\beta = \beta 0$.

Table D.3.3
Regression results for financial performance: ROA

Variables	Group means	Fama MacBeth	Random Effects	Random Effects with IV	Inverse Probability with IV
ISMFI	−0.013	−0.003	0.000	−0.058	−0.034
	(0.020)	(0.008)	(0.022)	(0.053)	(0.034)
GDPgrowth	−0.003	−0.000	0.001	0.001	0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Fees	−0.000	0.000	−0.000	−0.000**	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mktshare	−0.009	−0.019	−0.043	−0.043	−0.031*
	(0.023)	(0.011)	(0.045)	(0.045)	(0.017)
Mktsize	0.013***	0.016***	0.035***	0.030***	0.011***
	(0.004)	(0.002)	(0.006)	(0.005)	(0.003)
PAR	−0.332	−0.159***	−0.157***	−0.162***	−0.128***
	(0.202)	(0.023)	(0.032)	(0.033)	(0.036)
CAR	0.102***	0.099***	0.074**	0.077**	0.101***
	(0.023)	(0.020)	(0.036)	(0.031)	(0.013)
YGLP	−0.067	0.032	0.175**	0.144*	0.021
	(0.099)	(0.034)	(0.075)	(0.077)	(0.042)
GLP/assets	0.067**	0.087***	0.027	0.026**	0.028***
	(0.027)	(0.016)	(0.017)	(0.012)	(0.010)
DumAge	0.024	0.019***	0.000	0.002	0.018*
	(0.033)	(0.005)	(0.006)	(0.006)	(0.010)
DumReg	0.020	0.004	0.007	0.007	0.009
	(0.013)	(0.004)	(0.017)	(0.016)	(0.009)
Constant	−0.276***	−0.355***	−0.657***	−0.573***	−0.239***
	(0.092)	(0.055)	(0.123)	(0.090)	(0.039)
Time dummies	Yes	Yes	Yes	Yes	Yes
Observations	3,228	3,228	3,228	3,228	3,203
R-squared	0.164	0.281	0.074	0.135	0.098
Number of MFIID/ groups	516	14	516	516	511
Weak identification test					
F-statistic of excluded instruments				27.90***	12.75***
Stock-Yogo critical values (TSLS Bias)				11.57	11.57
Stock-Yogo critical values (TSLS Size)				11.59	11.59
Overidentification test of all instruments					
Hansen Statistic				2.535	0.060
P-value Hansen test				0.111	0.807

Notes: * refers to significant at 0.10%; ** significant at 0.05%; *** significant at 0.01%. Standard errors for Group means and RE estimates are based on a bootstrapping method; For Random Effects with IV and Inverse Probability with IV standard errors are robust clustered standard errors (with MFI as cluster). *Group means* refers to a between estimator (results based on Group means); *Fama MacBeth* refers to results using the Fama MacBeth method; *Random Effects* refers to a random effects panel estimate; *Random Effects with IV* refers to a random effects with instruments panel estimate and *Inverse Probability with IV* refers to panel estimate that combines inverse probability weighting and instruments. The Stock-Yogo TSLS Bias critical values are critical values for the Weak Instrument Test Based on TSLS Bias: Significance level is 5%; The critical value is a function of the number of included endogenous regressors (in our case 1), the number of instrumental variables (in our case 2), and the desired maximal bias of the IV estimator relative to OLS (in our case 1%). The critical value is obtained from Skeels and Windmeijer (2018) as Stock-Yogo do not present relative bias tables for 2 instrumental variables (it present bias tables only for 3 or more instrumental variables).The Stock-Yogo TSLS Size critical values are critical values for the Weak Instrument Test Based on TSLS Size: Significance level is 5%; The critical value is a function of the number of included endogenous regressors (in our case 1), the number of instrumental variables (in our case 2), and the desired maximal size (in our case 15%) of a 5% Wald test of $\beta = \beta 0$.

D.4. Results for MFIs offering only Sharia compliant microfinance products

Table D.4.1
Regression results for outreach: ALBGNI.

Variables	Group means	Fama MacBeth	Random Effects	Random Effects with IV	Inverse Probability with IV
Sharia compliant	−0.107	−0.107**	−0.124	−1.697***	−1.363***
	(0.237)	(0.045)	(0.121)	(0.637)	(0.465)
GDPgrowth	0.184	0.017	0.009**	0.010**	0.006
	(0.138)	(0.010)	(0.004)	(0.004)	(0.011)
Mktshare	1.721**	0.689***	−0.242**	−0.152	0.679***
	(0.675)	(0.079)	(0.120)	(0.111)	(0.245)
Mktsize	0.058	0.076***	0.084***	0.081***	0.044*
	(0.051)	(0.011)	(0.023)	(0.020)	(0.023)
PAR	−0.021	0.557	−0.181	−0.175**	0.187**
	(0.867)	(0.417)	(0.115)	(0.082)	(0.083)
CAR	−0.339	−0.157***	0.075	0.059	−0.148
	(0.232)	(0.037)	(0.079)	(0.074)	(0.132)
YGLP	−0.013	−0.619***	−0.231***	−0.164*	−0.544***
	(0.607)	(0.111)	(0.078)	(0.098)	(0.175)
GLP/assets	−0.885*	−0.403***	0.028	0.017	−0.194*
	(0.466)	(0.113)	(0.048)	(0.036)	(0.107)
DumAge	−0.099	−0.147***	−0.009	−0.026	−0.198**
	(0.175)	(0.038)	(0.044)	(0.048)	(0.089)
DumReg	0.271***	0.301***	0.401***	0.364**	0.276***
	(0.104)	(0.039)	(0.145)	(0.145)	(0.069)
Constant	1.317	−0.393*	−0.766**	−0.633**	−0.364
	(5.328)	(0.212)	(0.314)	(0.278)	(0.383)
Time dummies	Yes	Yes	Yes	Yes	Yes
Observations	4,680	4,680	4,680	4,680	4,637
R-squared	0.175	0.134	0.036	0.026	0.038
Number of MFIID/ groups	571	18	571	571	563
Weak identification test					
F-statistic of excluded instruments				20.88***	9.96***
Stock-Yogo critical values (TSLS Bias)				11.57	9.02
Stock-Yogo critical values (TSLS Size)				8.75	8.75
Overidentification test of all instruments					
Hansen Statistic				0.984	4.269
P-value Hansen test				0.321	0.039

Notes: * refers to significant at 0.10%; ** significant at 0.05%; *** significant at 0.01%. Standard errors for Group means and RE estimates are based on a bootstrapping method; For Random Effects with IV and Inverse Probability with IV standard errors are robust clustered standard errors (with MFI as cluster). *Group means* refers to a between estimator (results based on Group means); *Fama MacBeth* refers to results using the Fama MacBeth method; *Random Effects* refers to a random effects panel estimate; *Random Effects with IV* refers to a random effects with instruments panel estimate and *Inverse Probability with IV* refers to panel estimate that combines inverse probability weighting and instruments. The Stock-Yogo TSLS Bias critical values are critical values for the Weak Instrument Test Based on TSLS Bias: Significance level is 5%; The critical value is a function of the number of included endogenous regressors (in our case 1), the number of instrumental variables (in our case 2), and the desired maximal bias of the IV estimator relative to OLS (in this case 1% and 5%, respectively). The critical value is obtained from Skeels and Windmeijer (2018) as Stock-Yogo do not present relative bias tables for 2 instrumental variables (it present bias tables only for 3 or more instrumental variables).The Stock-Yogo TSLS Size critical values are critical values for the Weak Instrument Test Based on TSLS Size: Significance level is 5%; The critical value is a function of the number of included endogenous regressors (in our case 1), the number of instrumental variables (in our case 2), and the desired maximal size (in our case 20%) of a 5% Wald test of $\beta = \beta 0$.

Table D.4.2
Regression results for outreach: LNNAB.

Variables	Group means	Fama MacBeth	Random Effects	Random Effects with IV	Inverse Probability with IV
Sharia compliant	0.459**	0.264***	0.033	3.827***	4.115***
	(0.203)	(0.073)	(0.175)	(0.905)	(1.227)
GDPgrowth	0.130***	0.058***	−0.006*	−0.006*	0.060***
	(0.041)	(0.015)	(0.003)	(0.003)	(0.017)
Mktshare	−0.859**	−0.354***	0.392***	0.372***	−0.297
	(0.386)	(0.091)	(0.099)	(0.094)	(0.336)
Mktsize	0.749***	0.702***	0.747***	0.755***	0.839***
	(0.045)	(0.032)	(0.030)	(0.027)	(0.038)
PAR	−1.586**	−1.408***	−0.043	−0.041	−0.679***
	(0.712)	(0.264)	(0.112)	(0.095)	(0.214)
CAR	−0.336	−0.373***	−0.105	−0.099	−0.309
	(0.242)	(0.061)	(0.083)	(0.076)	(0.236)
YGLP	0.088	0.512**	0.328***	0.275**	0.541**
	(0.490)	(0.210)	(0.092)	(0.112)	(0.268)
GLP/assets	0.615***	0.645***	0.445***	0.447***	0.573***
	(0.206)	(0.103)	(0.167)	(0.144)	(0.151)
DumAge	0.468***	0.452***	0.066	0.072*	0.391***
	(0.159)	(0.103)	(0.041)	(0.042)	(0.132)
DumReg	−0.204*	−0.058	−0.267**	−0.188	−0.114
	(0.108)	(0.060)	(0.108)	(0.136)	(0.147)
Constant	4.497	−2.564***	−2.517***	−2.884***	−3.826***
	(5.351)	(0.485)	(0.405)	(0.382)	(0.572)
Time dummies	Yes	Yes	Yes	Yes	Yes
Observations	4,693	4,693	4,693	4,693	4,650
R-squared	0.626	0.616	0.587	0.766	0.547
Number of MFIID/ groups	571	18	571	571	563
Weak identification test					
F-statistic of excluded instruments				20.95***	9.95***
Stock-Yogo critical values (TSLS Bias)				11.57	9.02
Stock-Yogo critical values (TSLS Size)				8.75	8.75
Overidentification test of all instruments					
Hansen Statistic				0.037	1.201
P-value Hansen test				0.846	0.273

Notes: * refers to significant at 0.10%; ** significant at 0.05%; *** significant at 0.01%. Standard errors for Group means and RE estimates are based on a bootstrapping method; For Random Effects with IV and Inverse Probability with IV standard errors are robust clustered standard errors (with MFI as cluster). *Group means* refers to a between estimator (results based on Group means); *Fama MacBeth* refers to results using the Fama MacBeth method; *Random Effects* refers to a random effects panel estimate; *Random Effects with IV* refers to a random effects with instruments panel estimate and *Inverse Probability with IV* refers to panel estimate that combines inverse probability weighting and instruments. The Stock-Yogo TSLS Bias critical values are critical values for the Weak Instrument Test Based on TSLS Bias: Significance level is 5%; The critical value is a function of the number of included endogenous regressors (in our case 1), the number of instrumental variables (in our case 2), and the desired maximal bias of the IV estimator relative to OLS (in this case 1% an d5% respectively). The critical value is obtained from Skeels and Windmeijer (2018) as Stock-Yogo do not present relative bias tables for 2 instrumental variables (it present bias tables only for 3 or more instrumental variables).The Stock-Yogo TSLS Size critical values are critical values for the Weak Instrument Test Based on TSLS Size: Significance level is 5%; The critical value is a function of the number of included endogenous regressors (in our case 1), the number of instrumental variables (in our case 2), and the desired maximal size (in our case 20%) of a 5% Wald test of $\beta = \beta 0$.

Table D.4.3
Regression results for Financial Performance: ROA

Variables	Group means	Fama MacBeth	Random Effects	Random Effects with IV	Inverse Probability with IV
Sharia compliant	−0.030	−0.021*	−0.035	−0.095	−0.057
	(0.046)	(0.012)	(0.038)	(0.077)	(0.052)
GDPgrowth	−0.002	0.001	0.001	0.001	0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Mktshare	−0.003	0.001	−0.001	−0.003	−0.019
	(0.024)	(0.012)	(0.036)	(0.034)	(0.018)
Mktsize	0.015***	0.010***	0.027***	0.023***	0.010***
	(0.005)	(0.003)	(0.005)	(0.004)	(0.002)
PAR	−0.218	−0.176***	−0.064	−0.067*	−0.007
	(0.190)	(0.044)	(0.046)	(0.040)	(0.024)
CAR	0.097***	0.056***	0.065***	0.066***	0.086***
	(0.030)	(0.017)	(0.024)	(0.023)	(0.012)
YGLP	−0.059	−0.098	0.124***	0.106**	0.022
	(0.088)	(0.059)	(0.042)	(0.044)	(0.031)
GLP/assets	0.068***	0.092***	0.041***	0.040***	0.047***
	(0.025)	(0.018)	(0.011)	(0.011)	(0.008)
DumAge	−0.000	0.035***	0.005	0.006	0.015*
	(0.028)	(0.009)	(0.007)	(0.007)	(0.008)
DumReg	0.018	0.009	0.011	0.011	0.012
	(0.014)	(0.012)	(0.015)	(0.015)	(0.008)
Constant	−0.189	−0.263***	−0.424***	−0.374***	−0.178***
	(0.274)	(0.061)	(0.085)	(0.060)	(0.059)
Time dummies	Yes	Yes	Yes	Yes	Yes
Observations	4,379	4,379	4,379	4,379	4,338
R-squared	0.143	0.214	0.066	0.094	0.082
Number of MFIID/ groups	563	18	563	563	556
Weak identification test					
F-statistic of excluded instruments				19.37***	8.97***
Stock-Yogo critical values (TSLS Bias)				11.57	7.85
Stock-Yogo critical values (TSLS Size)				8.75	8.75
Overidentification test of all instruments					
Hansen Statistic				6.092	1.214
P-value Hansen test				0.014	0.271

Notes: * refers to significant at 0.10%; ** significant at 0.05%; *** significant at 0.01%. Standard errors for Group means and RE estimates are based on a bootstrapping method; For Random Effects with IV and Inverse Probability with IV standard errors are robust clustered standard errors (with MFI as cluster). *Group means* refers to a between estimator (results based on Group means); *Fama MacBeth* refers to results using the Fama MacBeth method; *Random Effects* refers to a random effects panel estimate; *Random Effects with IV* refers to a random effects with instruments panel estimate and *Inverse Probability with IV* refers to panel estimate that combines inverse probability weighting and instruments. The Stock-Yogo TSLS Bias critical values are critical values for the Weak Instrument Test Based on TSLS Bias: Significance level is 5%; The critical value is a function of the number of included endogenous regressors (in our case 1), the number of instrumental variables (in our case 2), and the desired maximal bias of the IV estimator relative to OLS (in this case 1% and 10% respectively). The critical value is obtained from Skeels and Windmeijer (2018) as Stock-Yogo do not present relative bias tables for 2 instrumental variables (it present bias tables only for 3 or more instrumental variables). The Stock-Yogo TSLS Size critical values are critical values for the Weak Instrument Test Based on TSLS Size: Significance level is 5%; The critical value is a function of the number of included endogenous regressors (in our case 1), the number of instrumental variables (in our case 2), and the desired maximal size (in our case 20%) of a 5% Wald test of $\beta = \beta0$.

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