Programa de Doctorado en Administración y Dirección de Empresas

TESIS DOCTORAL

Are microfinance institutions gender driven?

A clinical study

Doctoranda:

Sara Díaz-Pescuezo Martín

Directores de tesis:

Prof. Dr. D. José Manuel Feria Domínguez

Prof. Dr. D. David Naranjo Gil

Universidad Pablo de Olavide

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1. INTRODUCCIÓN

1.1. LAS MICROFINANZAS COMO VEHÍCULO PARA LA INCLUSIÓN FINANCIERA DE LAS MUJERES

En los últimos años, el uso de las microfinanzas como herramienta para aliviar la pobreza y promover la inclusión financiera de colectivos en riesgo de exclusión social ha suscitado un interés, cada vez mayor, por parte de reguladores y representantes políticos internacionales. En la década los 90, el término microcrédito fue reemplazado por microfinanzas, en referencia a una amplia gama de servicios financieros para los colectivos más vulnerables, como crédito, ahorro, seguros y pensiones (Karim, 2011). En el marco de la globalización, las microfinanzas constituyen un enfoque dentro de las finanzas que promueven la inclusión y la democratización de los servicios financieros para aquellos segmentos de población excluidos por la banca comercial tradicional, en particular, personas con bajos ingresos y microempresas (Cuasquer y Maldonado, 2011). Ésta se canaliza a través de las instituciones microfinancieras (en adelante, IMFs) que trabajan para favorecer la inclusión financiera, la sostenibilidad de las microempresas y el desarrollo social con el fin de empoderar a los sectores más desfavorecidos (Jha, 2016). Los microcréditos están destinados a la financiación de pequeñas y microempresas, y se caracterizan por plazos de amortización muy cortos e importes reducidos. Según Nasrin et al. (2018), las microfinanzas son una bendición para los pobres, ya que les brinda alternativas financieras para facilitar el acceso al crédito que, de otro modo, no estaría disponible para ellos. Por lo tanto, actúa como una herramienta para reducir la pobreza. No obstante, Chikwira et al. (2022) puntualizan que una microfinanciación inadecuada puede aumentar los niveles de pobreza a largo plazo y plantea que las microfinanzas no se usan siempre de manera eficiente.

Según el Informe de la Cumbre de Microcrédito (2013), en 2011, casi 4.000 IMFs otorgaron crédito a más de 200 millones de personas, de las cuales el 60% pertenecen a los grupos más vulnerables y, en particular, alrededor de 82,3% son mujeres (Maes y

Reed, 2012). Según Rahman y Khan (2013; 2016), las mujeres que participan en estos programas de microcrédito pueden llevar una vida digna con mayor confianza.

Hoy en día, la participación de la mujer en el mercado laboral es un imperativo económico y social. Como argumenta Ban (2010), a menos que las mujeres y las niñas sean liberadas de la pobreza, será imposible lograr la paz, la seguridad y el desarrollo sostenible. Por lo tanto, la sostenibilidad de las IMFs irremediablemente se encuentra vinculada a las mujeres, al ser éstas las principales usuarias de los productos y servicios microfinancieros.

La literatura sobre economía del comportamiento muestra que el comportamiento económico difiere según el género (Hartarska et al., 2014). Con respecto al papel de la mujer en las microfinanzas, Batool (2015) apunta que existe una mayor aceptación hacia las mujeres directivas en comparación con el pasado. Abdullah y Quayes (2016) indican que la mayoría de los prestatarios de microcréditos son mujeres, y la prevalencia de mujeres prestatarias es aún mayor entre los muy pobres. Adusei et al. (2018) argumentan que la diversidad de género en la junta directiva es un factor importante de la estructura de capital de las IMFs y reduce su exposición al riesgo de quiebra. Janda et al. (2013) indican que las IMFs deben tener mujeres como clientes. Además, las mujeres son más confiables que los hombres para el pago de los préstamos, por lo que se reduce la cartera en riesgo (*Portfolio at Risk*, PaR).

En 2015, la Asamblea de las Naciones Unidas estableció la Agenda 2030, aprobada tras la firma de 193 jefes de Estado y de Gobierno mundiales. En dicha agenda se incluyen un conjunto de 17 Objetivos de Desarrollo Sostenible (en adelante, ODS) y 169 metas que conjugan las principales dimensiones del desarrollo sostenible. Es claramente una llamada a la acción para que todos los países promuevan un mundo mejor y más sostenible al abordar los desafíos globales como la pobreza y el hambre, la defensa de los derechos humanos, la igualdad de género y el empoderamiento de las mujeres y la reducción de desigualdades, entre otras metas. Además, incorporan una visión del crecimiento económico sostenible e inclusivo, respetuoso con el planeta y sus recursos naturales. En este sentido, las microfinanzas se consideran un vehículo óptimo para converger hacia dichos ODS, al aliviar la pobreza, promover la inclusión financiera, aumentar el empoderamiento de las mujeres y reducir la desigualdad (Littlefield et al., 2003; Dhakal, 2004).

Dentro de los 17 ODS, nuestra investigación se va a enfocar en cuatro de ellos principalmente; el Objetivo 1, que consiste en poner fin a la pobreza en todas sus formas en todo el mundo; el Objetivo 5, que propone promover la igualdad de género y empoderar a todas las mujeres; el Objetivo 8, que busca promover el crecimiento económico sostenido, inclusivo y sostenible, el empleo pleno y productivo, y el trabajo decente para todos; y por último, el Objetivo 10, que apunta a reducir la desigualdad dentro de los países y entre ellos. En este sentido, la experiencia internacional del microcrédito muestra que tiene un papel fundamental en el desarrollo productivo y social, especialmente en los sectores más vulnerables de la población (Lombardi, 2016).

1.2. LA DOBLE MISIÓN DE LAS IMFs

Las microfinanzas están dirigidas a clientes con escasos recursos, por lo que se identifican dos visiones: una dirigida al éxito del negocio emprendido por el cliente, y otra dirigida al objetivo social de mejorar la calidad de vida de los mismos. Por tanto, las IMFs se consideran organizaciones híbridas con la doble misión de sostenibilidad financiera y propósito social (Lam et al., 2019). En consecuencia, dentro de la literatura existente se diferencian dos corrientes principales:

La Escuela del Bienestar (*Welfarist School*) se centra en la demanda social de reducción de la pobreza (Morduch, 2000; Dunford, 1998; Woller et al., 1999; Brody et al., 2003). Este enfoque evalúa el éxito a través de la mejora social y el bienestar inmediato de los clientes. Por otro lado, la Escuela Institucionalista se enfoca en el requisito de viabilidad económica de la institución (Gonzalez-Vega, 1993; De Briey, 2005). Este enfoque evalúa el éxito por el progreso de la institución en el logro de la autosuficiencia financiera.

Las agencias enfatizan que las IMFs deben ser autosuficientes en la generación de ingresos de la cartera de préstamos para cubrir el coste de prestar dinero y reducir la dependencia de los subsidios externos. Esto puede distraer el objetivo de minimizar la pobreza, ya que implicaría que las IMFs fueran rentables. Los investigadores han llamado a este dilema la misión dual (*mission drift*), que enfatiza la sostenibilidad financiera de la IMF además del alcance social, generando un tema de actual debate (Gutiérrez-Nieto et al., 2007; Abate et al., 2014; Mia y Chandran, 2016). La doble misión de las IMFs no se puede cumplir de manera equilibrada (Austin et al., 2006; Wilson y Post, 2011), por lo que algunos autores temen este desequilibrio en la misión (Mersland y Strøm, 2009; Chahine y Tannir, 2010; Bensalem y Ellouze, 2017). De hecho, autores como Paxton (2003) rechazan que pueda lograrse un equilibrio entre la sostenibilidad financiera y el alcance social. Pero, por otro lado, Cull y Morduch (2007) argumentan que las IMFs podrían mantener la rentabilidad y el alcance social simultáneamente si no ofrecen crédito a una persona totalmente pobre.

En este contexto, Gutiérrez-Nieto, et al. (2009) estudian la relación entre eficiencia social y financiera en las IMFs, y la relación entre la eficiencia y otros indicadores, como la rentabilidad. Los resultados de su estudio revelan la importancia de la evaluación de la eficiencia social y subrayan que las IMFs tienen un doble papel financiero y social, y necesitan ser eficientes en ambos. Como complemento a lo anterior, Gutierrez-Goiria et al. (2017) analizan los determinantes de la eficiencia social y económica en las IMFs encontrando dos factores que mejoran su eficiencia relativa: el estatus legal y el mercado objetivo. La principal contribución de su investigación es involucrar a las IMFs para lograr sus objetivos sociales sin renunciar a la eficiencia económica, ya que ambas pueden ser complementarias. En esta línea, Dissanayake (2012) analiza las variables significativas de la rentabilidad para una muestra de IMFs de Sri Lanka. Para ello, utiliza ratios de rentabilidad y sostenibilidad; considerando como variables explicativas la eficiencia, productividad, estructura de financiación y ratios de calidad de la cartera. De igual forma, Kharti (2014), busca identificar las variables determinantes del desempeño financiero de las instituciones microfinancieras en Marruecos. Sus resultados muestran que variables como la Cartera en Riesgo (*Portfolio at risk, PaR*), la antigüedad de las IMFs, la participación del patrimonio neto en el total de activos, la productividad del personal, y el porcentaje de mujeres clientes afectan el desempeño financiero de las IMFs.

Aparte del hecho de que el crédito puede ayudar a los pobres a mejorar su bienestar, también puede evitar que los pobres queden excluidos del sistema financiero formal. Brau y Woller (2004) diferencian entre exclusión parcial y exclusión total, dependiendo del grado de desarrollo del país. En este sentido, nuestra investigación se centra en el estudio clínico de dos países con fuertes necesidades de desarrollo microfinanciero: Argentina, por ser el país de América Latina donde las microfinanzas son más recientes y están menos desarrolladas, y por tanto donde pueden tener un mayor recorrido; y Bangladesh, por ser la cuna de las microfinanzas y uno de los 50 países más pobres del mundo, donde las IMFs son cruciales para su transformación económica y social.

1.3. LAS MICROFINANZAS EN ARGENTINA

Navajas y Tejerina (2011) brindan información sobre el acceso a servicios financieros de la población de América Latina y el Caribe, incluidos los microemprendimientos. Su estudio revela que 5,4 millones de personas tienen acceso a servicios de microfinanzas. Sin embargo, los autores señalan la falta de consenso sobre la definición y medición de las microfinanzas en cada país. Latinoamérica se encuentra en su década de mayor crecimiento en microfinanzas, creciendo la cartera de 590 millones de dólares en el 2000 a más de 40.2 billones de dólares en el 2014 (Mix Market, 2016).

En comparación con otros países de América Latina, la microempresa en Argentina es una categoría socioeconómica relativamente reciente. En Argentina, la crisis económica que vivió el país, desde la segunda mitad de la década de 1990 hasta finales de 2001, agravó la pobreza, concentrando la economía en unos pocos sectores de la población y dando lugar a nuevas formas de supervivencia. Ello desencadenó un aumento del desempleo, a la par que un drástico aumento de la actividad del sector informal, tanto en términos sociales como en la contribución de dicho sector al PIB. El concepto de microempresa nació precisamente como fórmula para salir de la crisis.

Argentina ocupa el segundo lugar, después de Brasil, en el ranking de países latinoamericanos en cuanto al número de bancos comerciales. Si comparamos la experiencia reciente de Argentina con la de otros países de la región donde han florecido las microfinanzas (por ejemplo, Perú o Bolivia), encontramos que el sector de las microfinanzas está subdesarrollado y limitado al microcrédito, es decir, créditos destinados a microempresas en un corto período de tiempo. Concretamente, en 2004 se creó la Red Argentina de IMFs (RADIM), integrada por las principales IMFs. RADIM es una organización cuya misión consiste en posibilitar la articulación de las instituciones del sector microfinanciero, su fortalecimiento y participación en el lanzamiento de propuestas al Estado y la Sociedad Civil (Informe RADIM, 2017). Además, Argentina aprobó una ley de microcrédito en 2006 (Ley 26.117, titulada "Fomento del Microcrédito para el Desarrollo de la Economía Social") para orientar y adaptar las prácticas de microcrédito en el país y creó la Comisión Nacional de Microcrédito (CONAMI) para administrar el Programa Nacional de Microcrédito de Argentina. Este programa se diferencia de otros programas nacionales en el concepto de "microcrédito", diferenciándolo de las microfinanzas, ya que este término se refiere al otorgamiento de microcréditos por parte del Estado para pequeños préstamos, en un corto período de tiempo, a clientes con poca o ninguna garantía, basado en entrevistas personales y sin historial crediticio.

El otorgamiento de microcréditos en Argentina se realiza de tres formas: Consorcio, Redes y Banco de Buena Fe (CONAMI, 2012):

- El consorcio es administrado por una junta directiva y varias instituciones gubernamentales locales y provinciales sin ánimo de lucro que están interesadas en apoyar programas de microcrédito. Una desventaja de este modelo es que, a veces, los municipios o provincias opuestas se niegan a cooperar en la creación de consorcios en sus ciudades, lo que limita la difusión del microcrédito (Ahnen, 2017).
- La segunda forma de microcrédito es a través de redes, por áreas geográficas o por ramas de actividad empresarial, como la red local en Lomas de Zamora (Buenos Aires).
- La última forma de entrega de microcréditos es a través del "Banco de Buena Fe" o "banquitos". Este es un servicio ofrecido por organizaciones no gubernamentales, como las ONGs.

En las tres modalidades, CONAMI, que forma parte de la Secretaría de Desarrollo Social Federal, entrega los fondos directamente a los "organismos administrativos" (en adelante, OA). Las OAs prestan a organizaciones más pequeñas, "organizaciones implementadoras" (en adelante, OI) y luego, las OIs prestan a los empresarios (CONAMI, 2012).

Otros países latinoamericanos estructuran sus programas de microcrédito en torno a las IMFs, mientras que Argentina se centra en las agencias financieras. Desde CONAMI explican que la idea de que una microempresa de crédito tenga en su centro a las IMFs, refleja principios capitalistas y conservadores, que distan mucho de la sociedad democratizada que la izquierda ha construido políticamente. Es por eso por lo que Argentina no tiene muchas IMFs en comparación con la mayoría de los países latinoamericanos. De hecho, Argentina tiene el menor número de prestatarios de microcréditos per cápita entre los 21 países latinoamericanos y un alto nivel de demanda insatisfecha de servicios de microcrédito.

Las mujeres, junto con los jóvenes, son uno de los colectivos más afectados por la pobreza y el desempleo en Argentina. Los programas de reforma económica y desregulación han llevado a una reducción importante del empleo formal, que ha afectado principalmente a las mujeres, ya sea por su alta ocupación femenina, o por el hecho de que éstas, en general, trabajan en trabajos temporales y de menor nivel; es lo que se ha venido a llamar la "feminización de la pobreza". Por lo tanto, las mujeres se ven empujadas a buscar el sustento económico familiar en actividades del sector informal, en gran parte como microempresarias (Platteau et al., 2006).

1.4. LAS MICROFINANZAS EN BANGLADESH

Tras su independencia de Pakistán, Bangladesh se convierte en uno de los países más pobres del mundo y, a la vez, en la cuna de las microfinanzas. A finales de la década de los 70, el profesor Muhammad Yunus, premio Nobel de la Paz (2006), dirigía el proyecto "Jobra", junto con el Banco de Bangladesh y el "Swanirvar Bangladesh", que dio lugar a varias iniciativas solidarias. En 1983, el profesor Yunus fundó el Grameen Bank y, para el año 2000, ya contaba con más de 12.000 empleados y 1.175 sucursales. El propio Yunus era avalista de los préstamos que otorgaba a los más pobres, alejándose así de la banca comercial tradicional que requería garantías, e inaugurando una nueva forma de inclusión financiera.

La Fundación Palli Karma Sahayak (en adelante, PKSF) encargó una encuesta (1997-2001) a través del Instituto de Estudios de Desarrollo de Bangladesh (en adelante, BIDS) que cubría 3.026 hogares de una muestra de 91 aldeas. La encuesta concluyó que las microfinanzas ayudaron a los hogares participantes a obtener ingresos un 8 por ciento más altos que los generados por los no participantes. Además, los usuarios pudieron garantizar más empleo en sus propias fincas debido a su mejor acceso al mercado de arrendamiento de tierras. El estudio BIDS también concluyó que la participación en el programa aumentaba la posibilidad de que tanto los niños como las niñas se matricularan en las escuelas.

Las estrategias operativas básicas de PKSF son las siguientes:

- No presta dinero directamente a las personas sin tierra y sin bienes, sino que llega a sus grupos objetivo a través de sus organizaciones socias (en adelante, OS).
- Da un mayor impulso al desarrollo institucional, tanto de su propia capacidad como organización principal como de las capacidades de las OS.
- No favorece ningún modelo sino que se fomentan las innovaciones y los diferentes enfoques basados en la experiencia.
- Actúa como defensor de políticas y regulaciones apropiadas útiles para el sector de las microfinanzas.

Los estudios de evaluación independientes han demostrado que el programa de microfinanzas de PKSF implementado a través de sus OS ha ayudado a aliviar la pobreza en Bangladesh. La cobertura total de los programas de microfinanzas en Bangladesh es de aproximadamente 13 millones de hogares. De las diversas actividades de empleo, principalmente por cuenta propia, la pequeña empresa/comercio es la más importante y representa más del 40 por ciento de los fondos desembolsados por las IMFs.

En 2009, *Microfinance Information Exchange* (en adelante, MIX) publicó una clasificación compuesta del desempeño de las IMFs. MIX Global 100 intenta brindar una imagen compuesta del desempeño de las IMFs utilizando atributos como alcance, eficiencia y transparencia. Las instituciones de microfinanzas de alto desempeño buscan maximizar el desempeño en varias áreas, cómo mejorar el alcance, minimizar el riesgo, reducir costes y aumentar la rentabilidad. En la clasificación de países, Bangladesh ocupó el quinto lugar con cinco IMFs en el top 100 de las nueve IMFs clasificadas.

Aproximadamente la mitad de la población de Bangladesh vive por debajo del umbral de la pobreza, con un 80% en las zonas rurales, y la carga de la pobreza recae de manera desproporcionada sobre las mujeres. Khandker (2005) descubrió que el acceso a las microfinanzas contribuye a la reducción de la pobreza, especialmente para las mujeres participantes en un panel de datos de Bangladesh. De hecho, la literatura existente muestra que las mujeres son favorecidas como prestatarias debido a su tasa de recuperación del 97%, en comparación con el 89% de los hombres (Khandker et al., 1995). En 2006, Yunus ya legitimó el modelo de microfinanzas como clave para el empoderamiento económico y social de las mujeres.

Según Karim (2011), las microfinanzas brindan a las mujeres pobres los recursos para invertir en sus comunidades, familias y en la vida de sus hijos; de hecho, las mujeres pobres de Bangladesh han demostrado un gran espíritu empresarial notable y han pagado sus préstamos a una tasa asombrosa de 98%. Hasta febrero de 2004, PKSF ha desembolsado una cantidad cercana a los 276,87 millones de dólares entre 4,55 millones de prestatarios pobres, de los cuales alrededor del 90% son mujeres (Ahmed, 2009).

CAPÍTULO 2: OBJETIVOS DE LA INVESTIGACIÓN

2. OBJETIVOS DE LA INVESTIGACIÓN

El objetivo general de esta investigación es determinar las variables predictoras del desempeño financiero de las IMFs. Habida cuenta que las IMFs son organizaciones híbridas con la "misión dual" de sostenibilidad financiera, como lo establece la Escuela Institucional (Morduch, 2000; Dunford, 1998; Woller et al., 1999; Brody et al., 2003), y el propósito social de aliviar la pobreza, como lo establece la Escuela de Bienestar (Gonzalez-Vega, 1993; De Briey, 2005), nos enfocamos particularmente en esclarecer si determinadas variables sociales, medidas a través de diversos ratios de género, son significativas para predecir dicho rendimiento financiero, y contribuir, de esta forma, a cumplir con la doble misión de las IMFs.

En el primer artículo, investigamos los determinantes del desempeño financiero en términos de rentabilidad económica (en adelante, ROA), y lo llevamos a cabo utilizando una muestra de 18 IMFs en Argentina entre 2002 y 2018, periodo en el que las instituciones de microfinancieras despegan en el país. Añadimos dos variables sociales independientes para capturar la profundidad del alcance, como la proporción de mujeres prestatarias y el tamaño promedio de la cartera de préstamos dividido por el PIB per cápita argentino. Además, incorporamos otros atributos independientes, comúnmente utilizados en la literatura existente (tamaño, eficiencia, solvencia, productividad y calidad de la cartera de crédito a 30 días), pero también enriquecimos nuestro análisis con dos variables macroeconómicas (tasa de interés real y tasa de desempleo), y con una variable ficticia para evaluar el posible impacto de la crisis internacional. Para hacer esta predicción usamos técnicas de minería de datos; en particular, el algoritmo Random Forest (en adelante, RF).

En el segundo artículo, la investigación se centró en predecir el rendimiento financiero ajustado al riesgo de las IMFs, representado por la relación del rendimiento de los activos dividida por la cartera en riesgo de 30 días (ROA/PaR30). Esta investigación se llevó a cabo en una muestra de 30 IMFs en Bangladesh para el período comprendido entre 2011 y 2018. Utilizamos en nuestro modelo cuatro variables de género, como el números de prestatarias femeninas, las mujeres directivas, las gerentes y las oficiales de crédito, para evaluar el impacto potencial de tales variables en el desempeño ajustado al riesgo. También incluimos otros atributos independientes, comúnmente utilizados en la literatura existente (tamaño, eficiencia, solvencia y productividad). Para hacer esta predicción, usamos los algoritmos Support Vector Regression (en adelante, SVR) y RF, con la idea de seleccionar el mejor modelo predictor.

CAPÍTULO 3: MARCO TEÓRICO

3. MARCO TEÓRICO

Para la presente tesis, el marco teórico se agrupa en los siguientes puntos:

a) LA AGENDA 2030 Y LA IMPORTANCIA DE LAS MICROFINANZAS

En 2015, la Asamblea de las Naciones Unidas estableció la Agenda 2030, aprobada tras la firma de 193 jefes de Estado y de Gobierno mundiales. En dicha agenda se incluyen un conjunto de 17 ODS y 169 metas que conjugan las principales dimensiones del desarrollo sostenible.

Las microfinanzas constituyen un enfoque dentro de las finanzas que promueven la inclusión y la democratización de los servicios financieros para aquellos sectores generalmente excluidos por la banca comercial tradicional; en particular, personas con bajos ingresos y microempresas (Cuasquer y Maldonado, 2011). Ésta se canaliza a través de las IMFs que trabajan para favorecer la inclusión financiera, la sostenibilidad de las microempresas y el desarrollo social con el fin de empoderar a los sectores más desfavorecidos (Jha, 2016).

Dentro de los 17 ODS, nos vamos a centrar en el Objetivo 1, el Objetivo 5, el Objetivo 8 y el Objetivo 10. Las microfinanzas se consideran un vehículo óptimo para cumplir estos ODS establecidos, al aliviar la pobreza, promover la inclusión financiera, aumentar el empoderamiento de las mujeres y reducir la desigualdad (Littlefield et al., 2003; Dhakal, 2004). Además, la experiencia internacional del microcrédito muestra que tiene un papel fundamental en el desarrollo productivo y social, especialmente en los sectores más vulnerables de la población (Lombardi, 2016).

b) PREDICCIÓN DEL RENDIMIENTO FINANCIERO Y SOCIAL DE LAS IMFs A TRAVÉS DEL PAPEL DE LAS MUJERES EN LAS MICROFINANZAS

El indicador común de desempeño financiero es el rendimiento de los activos (ROA), que refleja el margen de beneficio, así como la eficiencia de la institución (Bruett, 2005;

Hartarska, 2005; Lafourcade et al., 2005; Mersland y Strøm, 2009; Im y Sun, 2015). Según Lam et al (2019), el ROA es una mejor medida del desempeño financiero de las IMFs que el retorno sobre el capital (ROE). De hecho, el valor del ROE puede ser engañoso: un rendimiento positivo del capital puede o no implicar necesariamente un alto desempeño financiero de la IMF en el caso de que la IMF tenga ingresos negativos y un valor contable negativo del capital, posiblemente debido a años de pérdidas recurrentes.

Por otro lado, la cartera en riesgo (PaR) es un medida de la calidad de la cartera de crédito. La cartera en riesgo de más de 30 días (en adelante, PaR30) representa el porcentaje del total de la cartera de crédito que tiene, al menos, un pago con más de 30 días de atraso. Cabe recordar que las operaciones de las IMFs se caracterizan por la lógica de los créditos revolventes, es decir, los fondos se reembolsan casi en su totalidad a través de créditos (Pitt y Khandker, 1998; Ghatak, 1999; Armendáriz de Aghion y Morduch, 2000; Cull et al., 2007). Dado que las IMFs deben ser sostenibles a largo plazo, es interesante explorar la relación ROA/PaR30 propuesta en el segundo artículo.

Para predecir el rendimiento financiero, medido a través de la rentabilidad (ROA) y del rendimiento ajustado al riesgo (ROA/PaR30), hemos considerado una serie de variables independientes comúnmente estudiadas en la literatura existente, como la solvencia (Rai y Rai, 2012), la eficiencia (Microrate y BIDS, 2003; Dissanayake y Anuranga, 2012; Rai y Rai, 2012; Edwards et al., 2009; Muriu, 2011; Gudeta, 2013), la productividad (Churchill, 2005; Schreiner, 2000; Norell, 2001; Ayayi y Sene, 2010), el tamaño (Demirguc-Kunt et al., 1999; Cull et al., 2007; Huq et al., 2017), y el rendimiento social (Schreiner, 2000; Tchakoute-Tchuigoua, 2010; Lam et al., 2019) de las IMFs.

Por otra parte, para aportar a la doble misión de las IMFs, hemos añadido a nuestro estudio determinadas variables sociales que hacen referencia al papel de las mujeres dentro de las microfinanzas como las mujeres prestatarias, las mujeres directivas, las mujeres gerentes y las mujeres oficiales de crédito. La primera se usó en ambos artículos mientras que el resto se incorporaron en el segundo artículo debido a la importancia que tuvo la proporción de mujeres prestatarias en el primer artículo. A continuación, se muestra la descripción de todas ellas:

- Mujeres prestatarias

Las prestatarias se encuentran entre las más pobres de la población y las más excluidas de la banca formal (Bhatt y Shui-Yan, 2001). Según D'Espallier et al. (2011) las mujeres generalmente tienen una mejor calificación crediticia en microfinanzas que los hombres, según un conjunto de datos de 350 IMFs en 70 países. De hecho, Grameen Bank cambió su enfoque hacia dicho colectivo después de experimentar problemas de pago por parte de los prestatarios hombres en sus primeros años (Armendáriz y Morduch, 2005). Las mujeres, especialmente las de países pobres, tienen una movilidad muy limitada en comparación con los hombres (Armendáriz y Morduch, 2005) debido a una mayor presión social para cuidar a sus hijos. Al tener menos movilidad y carecer de la capacidad financiera para reubicarse, las mujeres a menudo quedan atrapadas en un lugar donde la presión y la humillación son mayores si no pagan sus préstamos (Kutsoati y Morck, 2014). Es por eso por lo que se espera que una mayor participación de las mujeres redunde en mayores tasas de reembolso y, por lo tanto, en un mejor desempeño financiero de las IMFs.

- Mujeres directivas

Adams y Ferreira (2009) mostraron que las directivas tienen un impacto significativo en las aportaciones de la junta y los resultados de la empresa en una muestra de empresas estadounidenses, donde las directivas tienen mejores registros de asistencia que los directores masculinos. En este sentido, según Galbreath (2011), las mujeres directivas y el crecimiento económico, en términos de ROE (retorno sobre el capital), ROA (retorno sobre los activos) y valor de mercado del capital en libros, son un vínculo positivo en una muestra de empresas cotizadas. En la misma línea, Erhardt et al. (2003) señalaron una asociación positiva entre la diversidad de la junta y el indicador financiero del desempeño de 127 grandes empresas estadounidenses. Por todo ello, se espera un mayor rendimiento financiero cuanto más alto es el porcentaje de mujeres directivas.

- Mujeres gerentes

El papel de la mujer gerente también tiene relevancia en el desempeño financiero a lo largo de los años. Según Kalleberg y Leicht (1991), las empresas lideradas por mujeres no tenían más probabilidades de quebrar, ni menos éxito, que aquéllas gestionadas por hombres, según 411 empresas de Indiana. Watson y Robinson (2003) demostraron que, aunque las ganancias son significativamente más altas para las pequeñas y medianas empresas controladas por hombres, cuando se considera el riesgo, no hubo diferencias significativas entre el desempeño de los gerentes masculinos y femeninos. Más aún, Mersland y Strøm (2009) apostillan que el desempeño financiero mejora con directores locales en lugar de internacionales, un auditor interno en la junta y una directora general mujer. Strom et al. (2014) confirmaron la relación positiva entre las mujeres gerentes y el desempeño financiero de 329 IMFs en 73 países. En este sentido, se espera una relación directa entre el desempeño financiero de las IMFs y las mujeres gerentes

- Mujeres oficiales de crédito

Beck et al. (2013) evidencian una mejor capacidad de las funcionarias de crédito para construir relaciones de confianza con los prestatarios, por lo que los préstamos supervisados por éstas tienen una menor probabilidad de volverse problemáticos que los préstamos otorgados por agentes de crédito masculinos. Por ello, es de esperar que un mayor porcentaje de mujeres oficiales de crédito conlleve una mayor tasa de reembolso y, por tanto, a un mayor desempeño financiero ajustado al riesgo de las IMFs.

c) METODOLOGÍA

En el desarrollo de la investigación utilizamos una metodología basada en la Minería de Datos (*Data Mining*). El aumento del volumen y variedad de información almacenada en bases de datos digitales ha crecido de manera espectacular en la última década, siendo un recurso de gran utilidad para predecir el comportamiento de cualquier sistema en el futuro. Además, las empresas, en general, y las financieras, en particular, suelen generar grandes cantidades de información cuyo análisis e interpretación es imposible realizar de forma manual. Actualmente, la información y la explotación de datos se ha convertido en un activo para las organizaciones inmersas en un proceso de transformación digital. Fayyad et al. (1996) definen los procesos de Descubrimiento de Conocimientos en Bases de Datos (*Knowledge Discovery in Databases,* KDD), y lo definen como un proceso no trivial de identificación de patrones válidos, novedosos, potencialmente útiles y, en última instancia, comprensibles en los datos. Este proceso secuencial se articula en distintas etapas (Fayyad y Stolorz, 1997):

- Selección de datos: Esta etapa se centra en la recopilación de la información relacionada con la investigación que se pretende realizar y que suele provenir de bases de datos, bien de dominio público o privado. En esta etapa es importante la familiarización con el dominio del problema con el objetivo de realizar una selección de datos a partir de los cuales se pueda extraer conocimiento útil. En nuestro caso hemos utilizado la base de datos pública de Mix Market (https://databank.worldbank.org/source/mix-market).
- Preprocesamiento: La calidad del conocimiento descubierto no depende sólo del algoritmo de Minería de Datos utilizado sino también de la calidad de los datos. Debemos pues seleccionar un conjunto de datos adecuado para lo cual procederemos a cursar la siguiente secuencia:
    - Limpieza de datos (*Data cleaning*): Las bases de datos suelen contener datos no depurados, perdidos, etc. Se deben eliminar el mayor número posible de datos erróneos o inconsistentes e irrelevantes. Los objetivos son rellenar valores perdidos, suavizar el ruido de los datos, identificar o eliminar datos anómalos (*outliers*) y resolver inconsistencias. En nuestro caso, hemos usado la técnica de imputación múltiple por ecuaciones encadenadas (MICE) para rellenar valores ausentes o NaN. Este algoritmo, para cada columna que tiene algunos valores ausentes, se ajusta a una regresión lineal con los valores actuales, y, después, utiliza estas funciones lineales para imputar los valores ausentes con la predicción de dichos valores.
    - Transformación de los datos: Algunas de las operaciones típicas que se suelen realizar en esta fase de transformación son: la normalización, la

construcción de nuevas variables o la discretización. En nuestro caso, hemos llevado a cabo una normalización de datos Min_Max, donde convertimos los valores en un valor comprendido entre 0 y 1.

- Reducción de la dimensionalidad: En esta etapa el objetivo principal es obtener una representación reducida del conjunto de datos, de volumen mucho menor, pero sin perder información. En nuestro caso hemos dividido los datos en una muestra de entrenamiento (70%) y otra de validación (30%) para comprobar la robustez del algoritmo.

• Minería de Datos: La Minería de Datos es la etapa más importante del proceso KDD y su objetivo es producir nuevo conocimiento para la toma de decisiones, ya sea a través de:
    - Modelos predictivos: Pretenden estimar valores futuros o desconocidos de variables de interés, denominadas como variables objetivo o dependientes, usando otras variables o campos de la base de datos, referidas como variables independientes o predictivas (Rana et al. 2014; Talavera-Llames et al.,2016; Galicia et al., 2019):
    - Modelos descriptivos: Sirven para explorar las propiedades de los datos examinados, no para predecir nuevos datos (Martínez-Álvarez et al., 2007; Pérez-Chacón et al., 2016).

En el campo de las microfinanzas, encontramos algunos trabajos que ya aplican técnicas de minería de datos como Wu et al. (2010), Kiweu (2011), o más recientemente, Pietrapiana et al. (2021) y Chikwira et al. (2022).

En nuestro caso, en ambos artículos hemos usado un modelo predictivo, el algoritmo Random Forest (RF). Breiman (2001) define RF como una combinación de predictores de árboles de manera que cada árbol depende de los valores de un vector aleatorio muestreado de forma independiente y con la misma distribución para todos los árboles. Combinando un cierto número de árboles, la predicción final para la variable dependiente se obtiene como el promedio de las predicciones de los árboles individuales que forman el conjunto. El algoritmo Random Forest (RF), comúnmente utilizado tanto para la clasificación como para la regresión, funciona particularmente bien para datos de alta dimensionalidad. Es una combinación de árboles de decisión en los que se observa qué variable puede predecir una determinada variable objetivo. El algoritmo del modelo se inicia en el conjunto de datos original y para cada muestra aleatoria de los datos originales, se ajusta un modelo de árbol de clasificación y se hace una predicción para cada árbol atravesando su nodo hoja. La metodología basada en RF se considera uno de los algoritmos de aprendizaje más precisos, ya que ofrece algunas ventajas: se ejecuta de manera eficiente en grandes bases de datos, puede manejar miles de variables de entrada sin eliminación de variables, proporciona estimaciones de qué variables son importantes en la clasificación, funciona bien con datos numéricos y categóricos mixtos, no hace suposiciones sólidas sobre la escala y la normalidad de los datos entrantes que hacen avanzar la construcción del bosque y, por último, es intrínsecamente capaz de manejar los datos faltantes. Jiang et al. (2018) y Malekipirbazari y Aksakalli (2015) demuestran que el algoritmo Random Forest funciona mejor que otros modelos de clasificación tradicionales, como la regresión logística.

En el segundo artículo, quisimos ir un paso más allá y comparamos el algoritmo RF con otro modelo predictivo, el Support Vector Regression (SVR) que también es un poderoso recurso para resolver problemas de regresión, y que se ha aplicado ampliamente en varios campos como las finanzas, la medicina y la ingeniería (Zhang et al., 2019; Li et al., 2020). SVR es un tipo de algoritmo de aprendizaje supervisado propuesto por primera vez por Vapnik en 1995 (Vapnik, 1999). En SVR, el objetivo es encontrar una función que se aproxime mejor a los puntos de datos, tratando de minimizar los errores. La función está representada por una combinación lineal de funciones kernel, que mapean los datos de entrada en un espacio de mayor dimensión. Una de sus principales ventajas es su capacidad para manejar datos no lineales y no estacionarios.

CAPÍTULO 4: ARTÍCULOS ELABORADOS

4. ARTÍCULOS ELABORADOS

4.1. ARE MICROFINANCE INSTITUTIONS' FINANCIAL PERFORMANCE GENDER DRIVEN? EVIDENCE FROM ARGENTINA

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a) DATOS DE LA REVISTA

La revista ***Business Strategy & Development*** proporciona contribuciones originales para mejorar el desarrollo y contribuir a los objetivos de desarrollo nacionales e internacionales. Examina los vínculos entre la estrategia competitiva y el desarrollo con énfasis en el papel del sector privado en el alivio de la pobreza a través de modelos de negocio inclusivos y la mejora de los medios de vida de las poblaciones de bajos ingresos, considerando una amplia gama de necesidades sociales.

b) MÉTRICA

Se trata de una revista indexada, de la editorial Wiley, posicionada como Q1 en Scopus, en la categoría Economics, Econometrics and Finance, con un SRJ de 0.58 (2021).

c) ESTADÍSTICAS DEL ARTÍCULO A FECHA DE MARZO 2023

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Citas	1

Abstract:

This paper studies the determinants of financial performance (ROA) of 18 Argentine Microfinance Institutions (MFIs) from 2002 to 2018. We apply the random forest algorithm to predict the ROA of the Argentine MFIs, introducing two social variables to capture the depth of the outreach such as the female ratio and the average size of the loan portfolio divided by the GDP per capita. We also consider five other main explanatory variables, such as the size, efficiency, quality of loan portfolio, solvency, and productivity ratio, as well as macroeconomic variables. Although our results indicate that the quality of the loan portfolio and efficiency are the most important variables in predicting ROA, we find that social variables are also important; in particular, the female ratio, which is the third relevant predictor of ROA. In contrast, macroeconomic variables and the financial crisis turn out to be insignificant in our analysis.

Keywords: Microfinance Institutions (MFIs), Financial Performance, Depth of the Outreach, Gender, Random Forest (RF), Argentina.

1. Introduction

In recent years, the use of microfinance as a tool for alleviating people's poverty and promote their financial inclusion has gained increasing attention from both policymakers and regulators in many countries. Cámara and Tuesta (2015) define financial inclusion as a process that maximizes the access to and the use of financial services and minimizes unintended barriers.

Esquivias et al. (2020) examined the determinants of financial inclusion in Vietnam, Indonesia and the Philippines finding significant differences in term of financial access by gender, income, education, age, job status and location of individuals.

In 2011, Microfinance Institutions (hereafter, MFIs) provided microcredit to more than 124 million extremely poor households, according to the Microcredit Summit Report (2013). The World Bank annual report (2013) highlighted that around 2.5 billion adults in the world are financially excluded.

Futhermore, in 2015, the United Nations Assembly established a set of 17 Sustainable Development Goals (SDG), adopting the 2030 Agenda for Sustainable Development.

They are a call to action for all countries to promote a better and more sustainable world by addressing the global challenges such as poverty, inequality, climate, environmental degradation, prosperity, and peace and justice. Mahida et al. (2021) describes the pathways to ensure a sustainable future in India and states that the expansion of microfinance, along with branchless banking and mobile device-based financial services can improve financial inclusion. In particular, *Goal 8* seeks to promote sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all; and *Goal 10* aims to reduce inequality within and between countries. In this sense, the international experience of microcredit shows that it has a fundamental role in productive and social development, especially in the most vulnerable sectors of the population (Lombardi 2016). The beginning of microcredit was in Bangladesh. When Bangladesh became independent from Pakistan, it became a country overwhelmed by poverty. Muhammad Yunus founded Grameen Bank in 1983 and by 2000, it had more than 12,000 employees and 1,175 branches. Yunus was a guarantor of the loans he granted to the poor he identified. Grameen Bank is therefore considered to be based on trust rather than collateral, thus moving away from the traditional commercial bank known until then.

Microfinance is the part of finance that aims at the implementation of financial services on small scale. The microcredits are intended for the financing of small and microenterprises and are associated with very short repayment terms and small amounts (Lombardi, 2016). According to Nasrim et al. (2018), microfinance is a blessing for the poor, as it provides them with financial alternatives to facilitate access to credit that would otherwise be unavailable to them. Therefore, it acts as a vehicle to reduce poverty, especially in developing countries. According to the Microcredit Summit Report (2013), as many as 3703 MFIs provide microcredit to 200 million people, of which 60% belong to the poorest groups. Around 82.3% are women (Maes and Reed 2012) and according to Rahman and Khan (2013; 2016), women who participate in these microcredit programs can lead a dignified life with greater confidence.

Microcredit is aimed at clients with few resources, so two visions are identified: one aimed at the success of the business undertaken by the client, and the other aimed at the social objective of improving the quality of life of clients. There are two main approaches to microfinance in the existing literature. The Welfarist School focuses on the social demand for poverty reduction (Morduch 2000; Dunford1998; Woller et al. 1999; Brody et al. 2003). This approach evaluates success through social improvement and immediate well-being of clients. The Institutionalist School focuses on the economic viability requirement of the institution (Gonzales-Vega 1993; De Briey 2005). This approach evaluates success by the institution’s progress in achieving financial self-sufficiency. Donor agencies emphasize that MFIs must be self-sufficient in generating income from the loan portfolio to cover the cost of lending money and reduce dependence on external subsidies. This may hinder the goal of minimizing poverty, as it would make MFIs profit driven. The researchers have called this the "dual mission", which emphasizes the financial sustainability of the MFI in addition to the social outreach, although this is a matter of debate, and it is not yet clear that MFIs can achieve both objectives at the same time (Gutierrez-Nieto et al. al. 2007; Abate et al. 2014; Mia and Chandran 2016). Cull and Morduch (2007) argue that MFIs could maintain profitability and social reach simultaneously if they do not offer credit to a totally poor person. Paxton (2003) rejects that there can be a trade-off between financial sustainability and social outreach.

Apart from the fact that credit can help the poor improve their welfare, it can also prevent poor people from being left out of the formal financial system. Futhermore, Brau and Woller (2004) differentiate between partial exclusion and total exclusion, depending on the country’s development.

Navajas and Tejerina (2011) provide updated information on the population's access to financial services in Latin America and the Caribbean, including microentrepreneurs. Their study reveals that 5.4 million people have access to microfinance services. However, the authors point out the lack of consensus on the definition and measurement of microfinance in each country. In addition, they estimate the potential demand for microcredit in Latin America without discerning how much potential microcredit there is in each country, including Argentina.

According to Mixmarket (2010), MFIs in Argentina have just over 39,000 active borrowers and $40.4 million in outstanding loans. Compared to other Latin American countries, microenterprise in Argentina is a relatively recent socioeconomic category. Microenterprise activity is generally considered a refuge for the unemployed or for the poorer people who do not have access to the formal labor market. The growing importance of microenterprises, and of the so-called "self-consumption microenterprises", is directly related to the country's economic and social crisis. Thousands of people have lost their jobs in the formal sector and are trying to survive in the informal sector. It is urgent to expand credit lines and design new financial services focused on the microenterprise sector in Argentina. The economic crisis led to an increase in unemployment, generating a drastic increase in the informal sector activity both in social terms and in the contribution of this sector to gross domestic product. Women, along with young people, are the most affected by poverty and unemployment in Argentina. Economic reform and deregulation programs have led to a very large reduction in formal employment, which has mainly affected women, due to their high employment of women, or to the fact that they, in general, work in temporary and lower-level jobs (so-called "Feminization of Poverty"). Women are thus pushed to seek their livelihood in informal sector activities, largely as microentrepreneurs (Platteau et al. 2006). The international financial crisis jeopardized the sustained growth of microfinance in Argentina because the situation impacted the availability of funds in the international market to finance microcredit and forced MFIs to exercise their rigor in the selection of potential clients to avoid a portfolio of defaulters that could jeopardize their viability.

The main goal of this paper is to predict the financial performance, in terms of return on assets (hereafter, ROA), of 18 microfinance institutions (MFIs) in Argentina from 2002 to 2018, by using the random forest algorithm. Since MFIs are hybrid organizations with the dual mission of financial sustainability and social purpose, we introduce in our model two social variables such as a female ratio and a proxy for social performance, among others. We also consider macroeconomic factors, as well a dummy variable relating to the period of financial crisis period.

The paper is structured as follows: in section 2 we describe the design of our analysis; in section 3 we present the main results and findings; and in section 4 we summarize some main conclusions.

2. Literature review

There are few empirical studies exist in recent literature focused on the determinants of financial inclusion from a microeconomic perspective or on the impact of different factors on the participation in the formal financial system. According to Allen et al. (2014), a positive relationship between financial inclusion and access to formal financial services was found for 123 countries in terms of lower banking costs, less paperwork and greater proximity to bank branches. Cámara and Tuesta (2015) report similar results for Peruvian households, also identifying education and gender as relevant factors for financial inclusion. In a similar vein, an important factor in explaining financial inclusion is education, according to Hoyo et al. (2014). In their case study on Mexico, the fact that women receive income from work increases the probability of financial inclusion.

Microfinance has proven to be an effective mechanism for poverty reduction and promoter of social inclusion, although it is not a sufficient condition for achieving these goals (Quibria 2012).

Just as credit may help the poor improve their welfare, it can also prevent the poor from being left out of the formal financial system. Moreover, exclusion ranges from partial exclusion in developed countries to total or near-total exclusion in less developed countries (Brau and Woller 2004).

In terms of MFIs performance, Hartarska (2005) shows that the regulated MFIs provide lower ROA in Eastern Europe and Central Asia, finding insignificant evidence that the breadth of outreach is affected by regulations. In addition, Hartarska and Nadolnyak (2007) highlight that the regulations have no impact on the MFI financial performance, finding little evidence that regulated MFIs typically serve fewer poor borrowers.

According to Yunus (2007), the use of consumer protection law and disclosure practices, such as those generally used by the banking sector, help the lender to disclose loan information that allows for comparability and interest rate effectiveness. This is a way to make customers aware of the agreements and avoids exploitation. In addition, truthfulness, and disclosure practices in a competitive scenario are much more effective in lowering interest rates than interest rate ceilings. Therefore, before going to regulate interest rates, the government must necessarily make sure that it has the means to ensure that this provision is respected by all related parties. A regulation of interest rates must take into account the facets that ensure transparency (Cotler 2010). One of the studies by Hartarska et al. (2009) takes data for Eastern Europe and Central Asia from the Micro Banking Bulletin and describes the size of MFIs. They found that MFIs with higher total assets experience a decrease in their costs, indicating the benefits of scaling up. Mersland and Strøm (2010) found no substantial sign of mission drift and found that, although MFIs earn higher profits with larger loan size, this allows them to continue to target poor clients. Thus, the cost-benefit comparison allowed MFIs to stay on track by serving typically poor clients rather than targeting wealthier clients.

More specifically, there are several studies on the financial performance of MFIs. Cull et al. (2007) examine profitability and patterns of loan repayment and cost reduction on 124 MFIs in 49 countries. Their results show the possibility of making profits while helping the poorest, although there is a clear trade-off in this regard. Mersland and Strøm (2009) explore the relationship between firm performance and corporate governance of MFIs using a global data set of MFIs. The results show that performance improves with local directors more than with international directors, and with internal auditors and female CEOs. Mersland et al. (2011) find that MFI internationalization improves social performance but does not improve financial performance. Tchakoute (2011) investigates the relationship between the status of MFIs and their performance and shows that the performance of private firms is better than that of NGOs. Esubalew et al. (2013) examine the effect of competition among MFIs. Their results show a negative relationship between intense competition and MFI performance. Janda et al. (2013) indicate that MFIs should have women as clients. Microfinance offers an opportunity for empowerment. In addition, women are more reliable than men for loan repayment, so portfolio risk is reduced.

As a result of the inability of traditional and development banks to productively finance the low-income population, microfinance appears to be a continuum between the economies of socialism and pure capitalism (World Bank 2008). In general, the poor are unable to obtain money from formal money providers.

This is the main cause of the lack of access to credit that leads to persistent poverty traps and income inequality (Beck et al. 2007; World Bank 2008).

Based on the institutionalist school, one of the most recent studies is by Kharti (2014), who studies the determinants of the financial performance of 10 MFIs in Morocco during 2003-2010, finding that portfolio risk and MFI age are the key factors. They also find a significant impact of MFI solvency, staff productivity, and the number of female clients in the MFI financial sector. MFI financial performance is defined as the ability to cover its financial and operating costs. Dissanayake (2012) analyzed 11 MFIs in Sri Lanka, in the period of 2005-2010. In this study, profitability is measured by profitability and sustainability ratios. He found that the cost per borrower is a key determinant of return on equity and operational self-sufficiency. In addition, the operating expense ratio and depreciation ratios are determinants of return on equity, return on assets and profit margin. Pietrapiana et al. (2021) conducted a study on Peruvian MFIs where they analyzed the main factors that explain profitability, applying data mining techniques such as Random Forest, M5' and KNN algorithms, and finding relevant variables such as efficiency.

The common indicator of financial performance is the return on assets (ROA), which reflects the profit margin, as well as the efficiency of the institution (Bruett et al. 2005; Hartarska 2005; Lafourcade et al. 2005; Barres et al. 2005; Mersland and Strøm 2009, Im and Sun 2015).

According to Lam et al (2020), ROA is a better measure of the MFI financial performance than return on equity (ROE). In fact, the value of ROE can be misleading: a positive return on equity may or may not necessarily imply high financial performance of the MFI in the case where the MFI has both negative income and a negative book value of equity, possibly due to years of repeated losses resulting in negative retained earnings. Therefore, we consider ROA as the dependent variable in our model.

3. Microfinance in Argentina

Argentina is second only to Brazil in the ranking of Latin American countries in terms of the number of commercial Banks. If we compare Argentina's recent experience with that of other countries in the region where microfinance has flourished (e.g., Peru or Bolivia), we find that the microfinance sector is underdeveloped and limited to microcredit (The Economist Intelligence Unit 2010). Moreover, in many cases, the failure of Argentine MFIs to reach potential microcredit clients was due to a lack of knowledge of the potential and actual demand they faced (Grandes 2010).

Microcredit institutions gained significant momentum in the 1990s in Argentina. The ventures of that time were small businesses with scarce economic resources, mostly aimed at solving poverty problems in certain places rather than large projects. The economic crisis that the country experienced from the second half of the 1990s until the end of 2001 aggravated poverty, concentrating the economy in a few sectors of the population and giving rise to new ways of surviving. The concept of microenterprise was born to overcome the crisis. Therefore, mechanisms were needed to facilitate the development and consolidation of these microenterprises, new MFIs were born and the importance of these institutions for the country's development became evident. In 2004, the Argentine Network of Microcredit Institutions (Red Argentina de Instituciones Microfinancieras, RADIM) was created, made up of the main microfinance institutions. RADIM is a second-tier organization, whose mission is to enable the articulation of the institutions in the microfinance sector, their strengthening, and their active participation in launching proposals to the State and Civil Society (Report RADIM 2017).

That is why our study focuses on the period between 2002 and 2018; period in which microfinance institutions in Argentina take off in the country.

Latin America is in its decade of greatest growth in microfinance, growing the portfolio from 590 million dollars in 2000 to more than 40.2 billion dollars in 2014 (Mix Market 2016). Particularly, in Argentina, there is a high level of unmet demand for microcredit services. Argentina has the lowest number of microcredit borrowers per capita among the 21 Latin American countries. For this reason, Argentina passed a microcredit law in 2006 (Law 26.117, entitled "Promotion of Microcredit for the Development of the Social Economy") to guide and adapt microcredit practices in the country. Leftist ideology has played an important role in shaping the design and implementation of these microcredit policies in Argentina. Several studies suggest that leftist politicizes are more likely to include an important role for the state in terms of income redistribution, greater social inclusion, and poverty reduction.

In Argentina, apart from companies that intermediate certain banking transactions (mortgages and card payments), they do not carry out the main transactions that require an agent (cash withdrawals and deposits). All these companies operating in Argentina, such as Rapipago and Pago Fácil, are only payment networks, so financial inclusion does not extend through this channel. Moreover, distrust in financial institutions stands out as one of the reasons for not participating in the formal financial system. Within this category, only age appears as a significant trait: the older a person is, the more likely he or she is to recognize this reason as a determinant of financial exclusion.

Ronald Ahnen (2017) examined the impact of leftist politics on microfinance in Argentina to understand why microcredit has not grown as fast in this country. It was with the arrival of Néstor Kirchner to presidency in 2003 that microcredit was developed as an instrument of social inclusion. After the new law was passed in 2006, the National Microcredit Commission (CONAMI) was created to administer Argentina's National Microcredit Program. This program differs from other national programs in the concept of "microcredit", differentiating it from microfinance, as this term refers to the granting of microcredits by the State for small loans, in a short period of time, to clients with little or no collateral and based on personal interviews and no credit score. Microfinance in Argentina also includes the provision of credit and other financial services such as personal loans, life, and unemployment insurance (Gandulfo 2012). It also differs in those other Latin American countries structure their microcredit programs around MFIs, while Argentina focuses on financial agencies. From CONAMI they explain that the idea that a credit microenterprise has MFIs at its center, reflects capitalist and conservative principles, which are far from the democratized society that the left has built politically. That is why Argentina does not have many MFIs compared to most Latin American countries.

The granting of microcredit in Argentina is carried out in three ways: Consortium, Networks and Good Faith Bank (CONAMI, 2012). The consortium is managed by a board of directors and several local and provincial non-profit government institutions that are interested in supporting microcredit programs. A disadvantage of this model is that sometimes opposing municipalities or provinces refuse to cooperate in the creation of consortia in their cities, which limits the diffusion of microcredit (Ahnen 2017).

The second form of microcredit is through networks, by geographical areas or by branches of business activity, such as the local network in Lomas de Zamora (Buenos Aires). The last form of microcredit delivery is through the "Banco de Buena Fe" or "banquitos". This is a service offered by non-governmental organizations, such as NGOs. In all three deliveries, modalities, CONAMI, which is part of the Federal Ministry of Social Development, delivers the funds directly to the "administrative organizations" (AOs). The OAs lend to smaller organizations, "implementing organizations" (IOs) and then, IOs lend to entrepreneurs (CONAMI 2012).

The international crisis that began in mid-2008, impacted Argentina as a "commercial crisis" (Ocampo 2009) and not as a monetary liquidity crisis. By the time the crisis broke out, Argentina had managed to accumulate a stock of international reserves and restore the liquidity and solvency of its financial system, expanding its margin of maneuver to face exchange or monetary stress (Abeles 2009). Argentina grew sustainably between 2003 and 2008, where it recorded the highest increase in GDP per capita, 8.5% on average, largely due to gross domestic fixed investment (GDFI), which doubled from 2003 to 2008.

4. Research design and methodology

Our analysis is based on a sample of 18 Argentine MFIs such as *Alternativa 3, Avanzar, BMM Córdoba, CEFAM, Columbia Microcréditos, Contigo Microfinanzas, Cordial Microfinanzas, Emprenda, Entre Todos, FIE Gran Poder, FPVS, Grameen Chaco, Grameen Mendoza, BMM Argentina (Intihuaca), OMLA, Pro Mujer, Progresar y Techo.* Data has been extracted from the Microfinance Information Exchange (MIX) database (www.mixmarket.org) for the period 2002-2018. In table 1, we describe the sample of MFIs, in terms of total assets (in USD), number of employees, and the averaged values of the variables used in our analysis.

Table 1: *Sample of Argentinian MFIs (Average 2002-2018)*

MFI Name	*Total Net Assets (in USD)*	*Number of employees*	*Social Performance*	*Female ratio*	*Solvency*	*Productivity*	*PaR30*	*Efficiency*
Alternativa 3	*259,731*	*5*	*2.58%*	*83.35%*	*71.12%*	*60.56*	*2.34%*	*70.02%*
Avanzar	*242,900*	*5*	*2.69%*	*61.39%*	*68.11%*	*85.77*	*6.07%*	*66.21%*
BMM Córdoba	*333,046*	*15*	*4.39%*	*71.00%*	*21.03%*	*61.22*	*9.60%*	*107.48%*
CEFAM	*401,684*	*6*	*8.08%*	*-11.72%*	*70.18%*	*57.4*	*-3.90%*	*56.96%*
Columbia Microcréditos	*2,677,811*	*39*	*12.24%*	*43.75%*	*-14.41%*	*57.80*	*30.56%*	*44.50%*
Contigo Microfinanzas	*3,097,745*	*23*	*8.79%*	*61.86%*	*62.85%*	*47*	*6.04%*	*122.26%*
Cordial Microfinanzas	*9,529,057*	*65*	*5.43%*	*48.07%*	*17.20%*	*79.25*	*5.79%*	*53.06%*
Emprenda	*4,862,937*	*52*	*9.47%*	*52.75%*	*23.72%*	*69.67*	*4.36%*	*57.99%*
Entre Todos	*107,688*	*3*	*4.67%*	*83.78%*	*52.86%*	*61.49*	*18.47%*	*505.61%*
FIE Gran Poder	*9,535,892*	*73*	*15.43%*	*42.00%*	*13.47%*	*73.37*	*1.65%*	*38.83%*
FPVS	*795,646*	*15*	*15.73%*	*33.55%*	*29.06%*	*53.8*	*7.07%*	*2545.58%*

Grameen Chaco	*82,931*	*3*	*-3.81%*	*98.59%*	*71.57%*	*66*	*11.58%*	*96.25%*
Grameen Mendoza	*587,123*	*19*	*5.02%*	*83.29%*	*51.81%*	*40.71*	*2.76%*	*231.94%*
Intihuaca - BMM Argentina	*922,796*	*27*	*4.30%*	*62.48%*	*18.59%*	*76.63*	*5.68%*	*96.77%*
OMLA	*2,196,946*	*23*	*12.18%*	*52.86%*	*31.41%*	*52.59*	*4.14%*	*59.99%*
Pro Mujer – ARG	*4,740,091*	*56*	*2.91%*	*99.98%*	*27.17%*	*170.64*	*0.42%*	*81.72%*
Progresar	*171,354*	*10*	*2.50%*	*74.26%*	*60.64%*	*44.8*	*-7.69%*	*164.29%*
Techo	*516,211*	*1*	*1.39%*	*93.51%*	*71.50%*	*97*	*73.57%*	*0.00%*

Since our sample contained some empty data, we had to fill the gaps by applying MICE (Multivariate Imputation by Chained Equations). To cope with the problems posed by the complexity of the data, it is convenient to specify the imputation model separately for each column of data. Thus, the "chained equations" technique was developed, which works as follows: given an empty data set in a random sample Y, the MICE algorithm obtains the distribution of the empty data set by iterating over the sample from conditional distributions of the form:

$$P(Y_1|Y_{-1},\theta_1) \ldots P\left(Y_p\middle|Y_{-p},\theta_p\right)$$

Starting from a simple observed marginal distribution, the t-iteration of the chained equations gives us a sampling as follows:

$$Y_p^{*(t)} \sim P(Y_p|Y_p^{obs}, Y_1^{(t)}, \ldots, Y_p^{(t)}, \theta_p^{*(t)})$$

where, $Y_j^{(t)} = (Y_j^{obs}, Y_j^{*(t)})$ is the imputed j-variable at t-iteration The number of iterations can be small; 30 in our case. The name chained equations refers to the fact that the MICE algorithm can be easily implemented as a concatenation of univariate procedures to complete the data. The algorithm runs m-flows in parallel, each of which generates a set of imputed data. (Buuren et al. 2011).

In our model, we selected 10 main independent variables to assess their potential impact on financial performance, measured in terms of ROA. In particular, we included two social performance measures as proxies for depth of outreach: the ratio of female borrowers and the average loan size divided by the Argentine GDP per capita.

Social Performance

In our model, we calculate average outstanding loan size normalized by GDP per capita as an inverse measure of social performance; in other words, the inverse of how much "good" the MFI is doing (Schreiner 2002; Tchakoute-Tchuigoua 2010). According to Lam et al. (2020), the average size of outstanding loan reveals the poverty status of MFI clients, as the "richer" poor tend to receive larger loans than the "poorer" poor. Consequently, larger loan sizes suggest that the MFI is serving the "richer" poor, thus doing less good socially.

Female ratio

The female ratio is defined as the percentage of female borrowers, measured by the number of active borrowers who are female divided by the number of active borrowers in the year. Female borrowers are among the poorest of population and the most excluded from formal banking, so this ratio is an appropriate proxy for depth of outreach (Bhatt and Shui-Yan 2001). Ayayi and Sene (2010) also use the female borrowers to capture client outreach.

Apart from social performance measures, we also consider other independent variables from the existing literature such as:

Solvency

The equity-to-assets ratio is the value of the MFI's equity divided by the value of its assets. It represents the amount of capital needed to cover additional unexpected losses in order to absorb potential shocks. (Online Accounting 2009; Michigan State University 2011). Rai and Rai (2012) found that the ratio of capital to asset was one of the key factors in the financial sustainability of MFIs.

Productivity

MFIs should adopt practices by focusing more on the client relationship to increase their performance management (Churchill 2000; Schreiner 2003; Norell 2001). The productivity ratio is measured by the number of active borrowers compared to the number of loan officers or staff (Ayayi and Sene 2010). This ratio works with the following logic: the higher the ratio, the more productive the MFI.

Loan portfolio quality (PaR30)

The portfolio at risk of more than 30 days (hereafter, PaR30) represents the percentage of the total loan portfolio that has at least one payment more than 30 days overdue. It should be recalled that MFI operations are characterized by the logic of revolving credits, i. e., loanable funds are almost entirely repaid through credits. Collective loans with joint and several guarantees are often used as a mechanism to minimize the risk of failure, improve the performance of MFI portfolios, and achieve financial viability (Pitt and Khandker 1998; Ghatak 1999; Armendariz de Aghion and Morduch 2000; Cull et al. 2007).

Size

There is a direct relationship between MFI size, measured by the logarithm of total assets, and its profitability (Demirguc-Kunt et al. 1999; Cull et al. 2007; Huq et al. 2017).

Efficiency

The measure of MFI efficiency is mainly determined by operating expenses relative to the loan portfolio (Microrate and BID 2003; Dissanayake and Anuranga 2012; Rai and

Rai 2012). Edwards et al. (2009) point to a positive relationship between financial performance and efficiency. Those MFIs that efficiently manage their operating expenses are profitable (Muriu 2011), earning profits due to low operating expenses (Gudeta 2013).

For convenience, we have also included two macroeconomic variables to test the potential impact on the dependent variable (ROA), such as the unemployment rate and the real interest rate, adjusted by the inflation rate.
Moreover, to enrich the conclusions, we have also differentiated between two main periods by defining a dummy variable: pre-crisis period of 2002-2007 and crisis period of 2008-2018, taking the values 0 and 1, respectively.
In table 2 we summarize the description of the variables:

Table 2: *Description of variables*

Dependent variable	
ROA	*Return on asset ratio = Net operating income / total asset*
Independent variables	
Social performance	*Average loan size divided by Argentinian GDP per capita*
Female ratio	*Female borrowers' ratio = Number of active borrowers who are women divided by the number of active borrowers in the year*
Solvency	*Equity to asset ratio = Total equity / total assets*
Productivity	*Productivity ratio = Number of active borrowers / total number of staff*
PaR30	*Portfolio at risk > 30 days = Outstanding balance on arrears over 30days + total gross outstanding refinanced (portfolio) / total gross portfolio*
Size	*Total net assets in the year (in USD)*
Efficiency	*Percent of operating expenses = Operating expenses / loan portfolio*

Macro-variables	
Real Interest rate	
Unemployment rate	
Dummy variables	
Crisis	*Pre-crisis period: 2002-2007 and Crisis period: 2008-2018*

In table 3, we summarize the values of the macroeconomic variables for the analyzed time horizon (2002-2018). In 2002, the highest real interest rate and unemployment rate, are registered due to the harsher impact of the Argentinean crisis (December 2001). After 2002, the impact of the international crisis on the macroeconomic variables, is milder than the Argentinean crisis itself.

Table 3: *Historical values of the macro-economic variables in Argentina*

Year	*Real interest*	*Unemployment*
2002	*16.18%*	*19.59%*
2003	*7.83%*	*15.36%*
2004	*-9.79%*	*13.52%*
2005	*-3.77%*	*11.51%*
2006	*-4.5%*	*10.08%*
2007	*-3.38%*	*8.47%*
2008	*-3.01%*	*7.84%*
2009	*0.24%*	*8.65%*
2010	*-8.57%*	*7.71%*
2011	*-7.77%*	*7.18%*
2012	*-6.75%*	*7.22%*
2013	*-5.49%*	*7.10%*
2014	*-11.6%*	*7.27%*
2015	*-1.31%*	*7.61%*
2016	*-7.01%*	*7.97%*
2017	*0.46%*	*8.35%*
2018	*6.07%*	*9.22%*

As for the methodology, we use an ensemble-based technique which is the Random Forest (RF) algorithm. Combining a certain number of trees, the final prediction for the dependent variable (ROA) is obtained as the average of the predictions of the individual trees that form the ensemble. Breiman (2001) defines RF as a combination of tree predictors such that each tree depends on the values of a random vector sampled independently and with the same distribution for all trees in the forest. The Random Forest algorithm, commonly used for both classification and regression, performs particularly well for high dimensionality data. It is a combination of decision trees in which one looks at which variable can predict a given target variable. The model algorithm bootstraps on the original data set. For each random sample of the original data, a classification tree model is fit, and a prediction is made for each tree by traversing to its leaf node.

The RF-based methodology is considered one of the most accurate learning algorithms, as it offers some advantages: it runs efficiently on large databases, it can handle thousands of input variables without variable elimination, it provides estimates of which variables are important in classification, it works well with mixed numerical and categorical data, it makes no strong assumptions about the scale and normality of the incoming data that advances the construction of the forest, and finally, it is inherently capable of handling missing data.

The RF model obtains a considerably higher accuracy prediction than the classification tree. As Jiang et al. (2018) and Malekipirbazari and Aksakalli (2015) demonstrate, Random Forest algorithm performs better than other traditional classification models, such as logistic regression and support vector machines.

We split the sample into cross-validation method as follows:

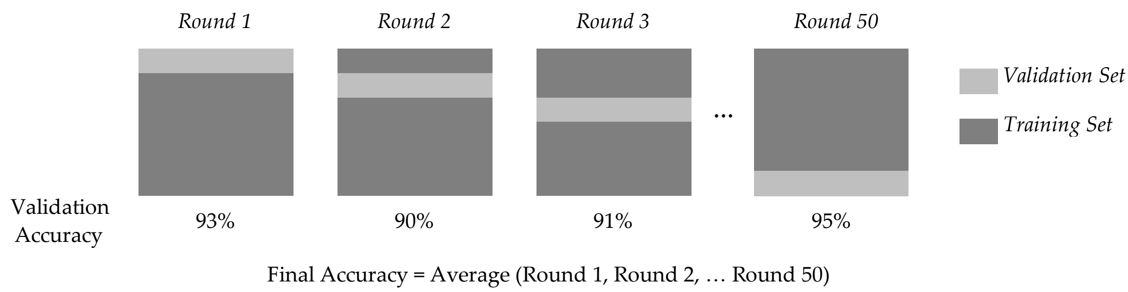


Figure 1: *Cross-validation procedure*

The cross-validation procedure consists of taking the original data and creating two separate sets from it: a training set and a validation set. The training set will be divided into *k* subsets and each *k* subset will be taken as the training set of the model, while the rest of the data will be taken as a validation set. This process will be repeated *k* times, in each iteration a different training set will be selected, while the rest of the data will be taken as validation set. Once the iterations are completed, the accuracy and error of each of the models is calculated, as well as the average of the *k* trained models.

The Random Forest algorithm creates a decision tree with each data set, resulting in different trees. When generating such trees, random variables are chosen at each node of the tree, and each tree provides a single vote for the best variable. The process is repeated for each of the trees to arrive at the result by averaging the votes of each tree and indicating the importance of each of the variables.

In this work, we have established 13 MFIs as the training set, and 5 MFIs as the validation set following the procedure illustrated in Figure 1. We divide our training set into 50 folds, and then, run the model iteratively in 50 rounds. Each time, we train the data on 49 of the folds and evaluate the 50th fold, i.e., the validation data. For example, in the fiftieth round we train on the first 49 folds and evaluate on the fiftieth. In the first round, we train on the second, third, fourth and fifth folds and evaluate on the first one. We repeated this procedure 4 more times, evaluating on a different fold each time. Finally, we averaged the performance on each of the folds to become the final validation metrics for the model.

Based on these assumptions, a model of MFI financial performance can be estimated with the following specification:

$$ROA_{it} = f\ (SOCIAL\_PERFORMANCE_{it} + FEMALE\_RATIO_{it} + SOLVENCY_{it} + PRODUCTIVITY_{it} + PaR30_{it} + SIZE_{it} + EFFICIENCY_{it} + REAL\_INTEREST_{it} + UNEMPLOYMENT_{it} + CRISIS_{it})$$

where,

$i = 1,\dots; N$ for each MFIs

$t = 1,\dots; T$ refers to the time period.

5. Results and main findings

According to Tukey (1977), Exploratory Data Analysis (EDA) is an essential step in any research analysis. The objective of EDA is to visualize and examine the data, beforehand. Table 4 provides a summary of the main statistics (mean, standard deviation, median, minimum, maximum and percentiles 25th and 75th) of the selected variables for all the MFIs.

Table 4: *Descriptive statistics*

	Mean	*S.D.*	*Min*	*P25*	*Med*	*P75*	*Max*
ROA	*-0.50*	*1.85*	*-7.46*	*-0.47*	*-0.13*	*0.03*	*7.90*
Size	*2,281,199*	*3,484,129*	*-211,423*	*259,731*	*587,123*	*2,850,147*	*20,944,952*
Social Performance	*0.06*	*0.08*	*-0.52*	*0.03*	*0.05*	*0.09*	*0.65*
Female ratio	*0.63*	*0.30*	*-1.96*	*0.48*	*0.62*	*0.83*	*1.04*
Solvency	*0.42*	*0.30*	*-1.57*	*0.20*	*0.42*	*0.68*	*1.00*
Productivity	*69.76*	*32.34*	*-1.91*	*53.20*	*61.36*	*79.25*	*216.00*
PaR 30	*0.10*	*0.19*	*-0.87*	*0.02*	*0.06*	*0.11*	*0.74*
Efficiency	*2.44*	*7.01*	*-0.84*	*0.53*	*0.75*	*1.22*	*57.14*
Real Interest	*-0.02*	*0.07*	*-0.12*	*-0.07*	*-0.04*	*0.00*	*0.16*
Unemployment	*0.10*	*0.03*	*0.07*	*0.08*	*0.08*	*0.10*	*0.20*

Churchill and Iacobucci (2005) stated that multicollinearity reduces the efficiency of the estimates, so we have tested for multicollinearity. In table 5 we illustrate the mutual correlation coefficients for the dependent and explanatory variables in our analysis. According to Kennedy (2008) and Pal and Soriya (2012), correlations should exceed the cut-off value of 0.8 to detect collinearity between two variables. Since all the correlation coefficients in the correlation matrix are less than 0.8, there is no multicollinearity problem.

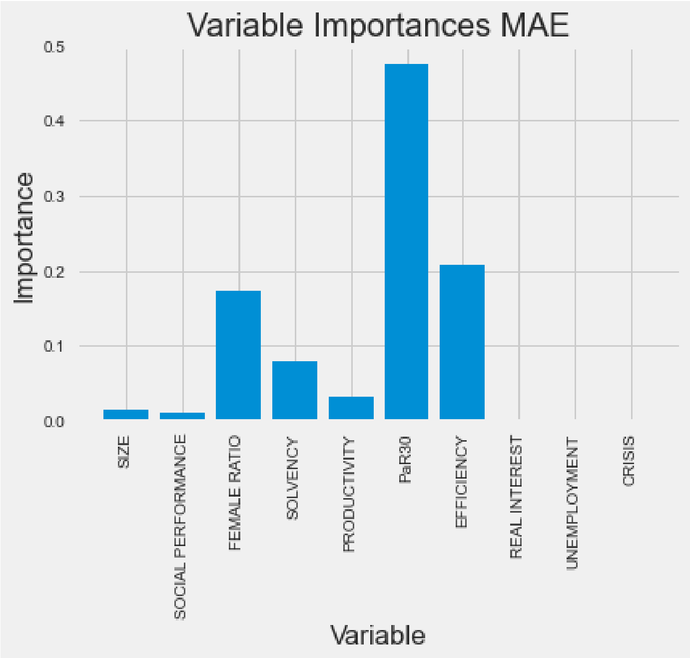
Table 5: *Correlation matrix*

	1	2	3	4	5	6	7	8	9	10
1. ROA	1									
2. SIZE	0.137229	1								
3. SOCIAL PERFORMANCE	0.175486	0.235358	1							
4. FEMALE RATIO	-0.53675	-0.16041	-0.40754	1						
5. SOLVENCY	-0.27592	-0.33054	-0.27126	0.193665	1					
6. PRODUCTIVITY	-0.142	0.241012	-0.19287	0.286992	-0.11685	1				
7. PaR30	-0.76441	-0.10846	-0.09707	0.255569	0.063018	0.181894	1			
8. EFFICIENCY	0.184027	-0.12351	0.043511	-0.20077	-0.10252	-0.07565	-0.0077	1		
9. REAL INTEREST	-0.00192	-0.05665	-0.05909	0.003335	-0.03841	-0.01887	-0.04438	-0.00108	1	
10. UNEMPLOYMENT	-0.02074	-0.10214	-0.02769	0.008977	-0.00575	-0.04202	-0.05882	-0.0005	0.698851	1

In order to calibrate the robustness of the RF algorithm we perform a back test on a subset of data. With N being the number of MFIs being the predictive (or estimated) values of ROA, y being the actual values of ROA, $|y_i - \hat{y}_i|$ being the mean of each set; the Root Mean Absolute Error (MAE) is calculated as:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i|$$

The following figure summarizes all the results of the Random Forest algorithm:




```
Variable: PaR30                 Importance: 0.48
Variable: EFFICIENCY            Importance: 0.21
Variable: FEMALE RATIO          Importance: 0.17
Variable: SOLVENCY              Importance: 0.08
Variable: PRODUCTIVITY          Importance: 0.03
Variable: SIZE                  Importance: 0.02
Variable: SOCIAL PERFORMANCE    Importance: 0.01
Variable: REAL INTEREST         Importance: 0.0
Variable: UNEMPLOYMENT          Importance: 0.0
Variable: CRISIS                Importance: 0.0
```

Figure 2*: Independent variables ordered by importance*

The number of occurrences of a feature variable is proportional to the importance measure of a feature variable. This is because the algorithm selects the feature at any specific node position based on maximum information gain. The measure gives an indication of which observations are close to each other based on the class predictions made on the tree collection. Each random sample has a set of out-of-bag observations that are excluded due to random sampling. For each tree, predictions are made based on the out-of-bag observations.

In figure 3, we plot one of the decision trees obtained by RF, highlighting that the loan portfolio quality (PaR30) is the most important variable, followed by the efficiency and the female ratio in the ROA prediction process. Macro variables and the financial crisis are irrelevant in our analysis.

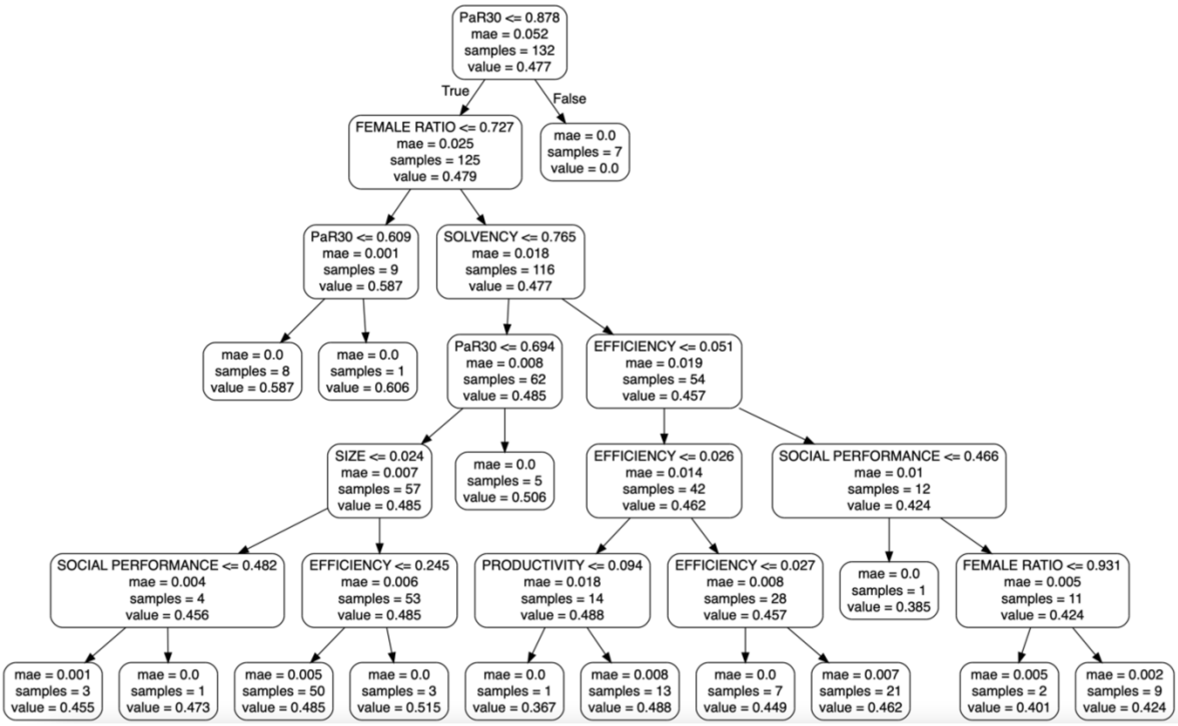


Figure 3: *Decision tree*

Cross-prediction accuracy (MAE) is 93.3% as illustrated by the scatter plot of actual ROA vs predicted ROA:

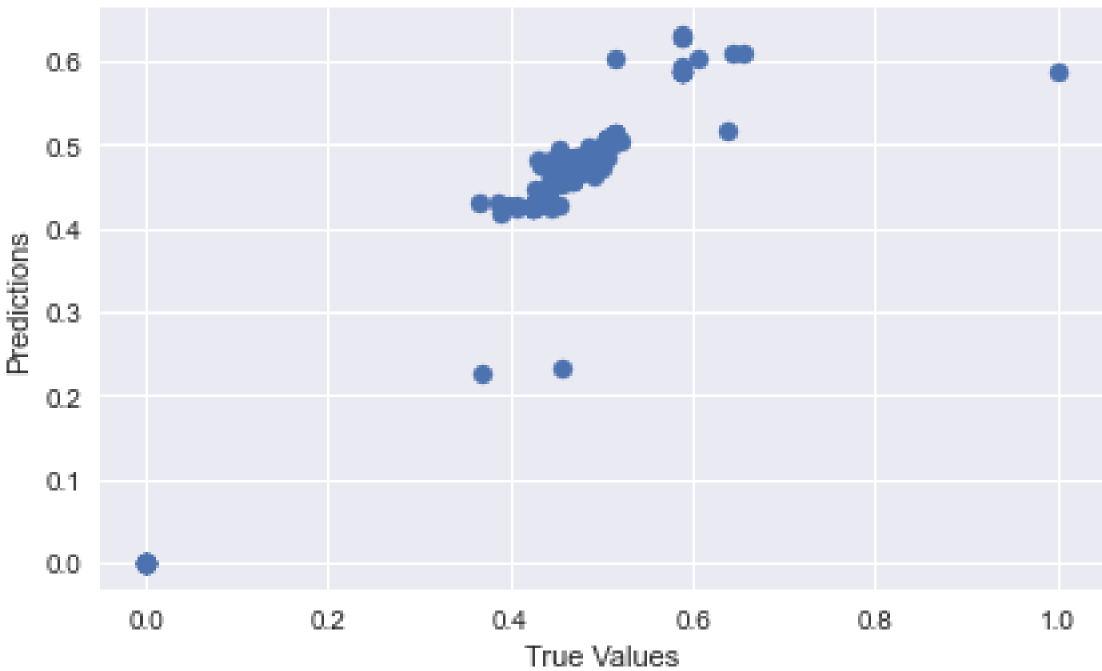


Figure 4*: Scatter plot*

6. Conclusions

In this paper, we investigate the key drivers of the financial performance in a sample of 18 MFIs in Argentina from 2002 to 2018. Addressing this variable through ROA, we apply an ensemble-based technique, the Random Forest algorithm (RF), to predict such a dependent variable, obtaining 93.3% of cross-validation accuracy. Since MFIs are hybrid organizations with the "dual mission" of financial sustainability (as stated by the Institutional School) and the social purpose of poverty alleviation (as stated by the Welfarist School), we particularly focus on two independent social variables to capture the depth of the outreach, such as the female ratio and the average loan portfolio size divided by the Argentine GDP per capita. We take into account other independent attributes, commonly used in the existing literature (size, efficiency, solvency, productivity and quality of the loan portfolio), but we also enrich our analysis with two macroeconomic variables (real interest rate and unemployment rate), as well as a dummy variable to assess the possible impact of the international crisis.

By running the RF algorithm we find that the quality of the loan portfolio (PaR30) is the most important variable in predicting ROA, being assigned 48% relative importance. The efficiency, measured by operating expenses relative to the loan portfolio, is the second most important variable, with 21% relative importance. In addition, we contribute to the existing debate in the literature to the extent that depth of outreach, proxied by the two social variables, is also important. Specifically, the female ratio, defined as the number of active borrowers who are women divided by the number of active borrowers in the year, is considered the third relevant predictor of ROA, obtaining 17% significance; in other words, gender is shown to be one of the main drivers of the financial performance of Argentine MFIs. The economic crisis has caused an increase in unemployment, generating a drastic increase in informal sector activity. Women, along with young people, are the most affected by poverty and unemployment in Argentina because they tend to work in temporary and lower-level jobs (the so-called feminization of poverty). Thus, women are pushed to seek their livelihoods in informal sector activities, largely as microentrepreneurs. Since women entrepreneurs face less availability of credit, microfinance institutions should facilitate credit to women. As a result, microfinance institutions pursuing this social objective will target women as clients while also ensuring their financial sustainability.

As included in the 2030 Agenda, in addition to Sustainable Development Goals 8 and 10 mentioned above, Goal 5 aims to promote gender equality. In this sense, microfinance institutions, in addition to poverty reduction, can provide an opportunity for women's empowerment. In addition, women are more reliable than men in repaying loans, thus reducing portfolio risk, and consequently improving the financial performance of MFIs, in terms of ROA.

With regard to solvency and productivity, they receive 8% and 3% relative importance, respectively, while productivity and size account for 2%. Finally, the social performance has 1% relative importance. Macro variables are not relevant in our model. We should keep in mind that the Argentine economy was previously affected by the Argentine crisis at the end of 2001. Consequently, from 2003 to 2018, the macroeconomic variables remain more or less stable over time, with the exception of 2002, when the historical values of these variables reach a significant peak. The financial crisis (dummy variable) turn out to be insignificant as well in our analysis.

This paper has important managerial implications for the strengthening of the Argentine microfinance sector, as it highlights the main drivers of financial performance. By setting strategic thresholds on 3 key variables (PaR30, efficiency and female ratio), MFIs managers can strive for long term financial sustainability of the MFI, as well as balance in its dual mission; social and economic.

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4.2. IS RISK-ADJUSTED FINANCIAL PERFORMANCE SENSITIVE TO GENDER? EVIDENCE FROM BANGLADESH MICROFINANCE INSTITUTIONS

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Abstract:	In this paper we explore the main gender drivers –Female board members, Female managers, Female loan officers, and Female borrowers– influencing the risk-adjusted performance, proxied by the ratio –ROA/PaR30–for a sample of 30 Bangladeshi MFIs from 2011 to 2018. By applying data mining techniques such as the Random Forest –RF– and the Support Vector Regression ¬–SVR– algorithms, we find that the female loan officers is the most important explanatory variable, followed by the solvency, the efficiency and the female borrowers, in this order, when predicting the MFI's risk-adjusted performance. Moreover, female board members and female managers are also significant but less than size, social performance and productivity. Since MFIs are hybrid organizations with the dual mission of financial sustainability and social purpose, the prediction of the risk-adjusted performace is crucial and has important managerial implications. We also find that RF algorithm provides a better fit than SVR, 79.6% in terms of mean absolute error –MAE–and is proved to be high sensitive to the gender key drivers.

ABSTRACT

In this paper we explore the main gender drivers –Female board members, Female managers, Female loan officers, and Female borrowers– influencing the risk-adjusted performance, proxied by the ratio –ROA/PaR30–for a sample of 30 Bangladeshi MFIs from 2011 to 2018. By applying data mining techniques such as the Random Forest –RF– and the Support Vector Regression –SVR– algorithms, we find that the female loan officers is the most important explanatory variable, followed by the solvency, the efficiency and the female borrowers, in this order, when predicting the MFI's risk-adjusted performance. Moreover, female board members and female managers are also significant but less than size, social performance and productivity. Since MFIs are hybrid organizations with the dual mission of financial sustainability and social purpose, the prediction of the risk-adjusted performace is crucial and has important managerial implications. We also find that RF algorithm provides a better fit than SVR, 79.6% in terms of mean absolute error –MAE–and is proved to be high sensitive to the gender key drivers.

KEYWORDS: Risk-adjusted financial performance, Microfinance institutions (MFIs), Gender, Random Forest, Support Vector Regression, Bangladesh

1. INTRODUCTION

In 2015, the United Nations Assembly established a set of 17 Sustainable Development Goals (SDG), adopting the 2030 Agenda for Sustainable Development. They are a call to action for all countries to promote a better and more sustainable world by addressing the global challenges such as poverty, inequality, climate change, environmental degradation, prosperity, and peace and justice. In this sense, the microfinance is considered an optimal vehicle to comply with some of the SDGs, by alleviating poverty, promoting the financial inclusion, and increasing women's empowerment and reducing inequality (Littlefield et al., 2003; Dhakal, 2004). Mahida et al. (2021) describes the pathways to ensure a sustainable future in India and states that the expansion of microfinance, along with branchless banking and mobile device-based financial services can improve financial inclusion. Lombardi (2016) point outs the strategic role of microcredits in productive and social development, especially in the most vulnerable sectors of the population.

Microfinance is the part of finance that focuses on the implementation of financial services on small scale. The microcredits are intended for the financing of small and microenterprises and are associated with very short repayment terms and small amounts. According to Nasrin et al. (2018), microfinance is a blessing for the poor, as it provides them with financial alternatives to facilitate access to credit that would otherwise be unavailable to them. Therefore, it acts as a tool to reduce poverty, especially in developing countries. According to the Microcredit Summit Report (2013), as many as 3703 MFIs provide microcredit to 200 million people, of which 60% belong to the poorest groups. Around 82.3% are women (Maes and Reed 2012) and according to Rahman and Khan (2013; 2016), women who participate in these microcredit programs can lead a dignified life with greater confidence.

Microcredit is aimed at clients with few resources, so two visions are identified: one aimed at the success of the business undertaken by the client, and the other aimed at the social objective of improving the quality of life of clients. There are two main approaches to microfinance in the existing literature. The Welfarist School focuses on the social demand for poverty reduction (Morduch 2000; Dunford1998; Woller et al. 1999; Brody et al. 2003). This approach evaluates success through social improvement and immediate well-being of clients. The Institutionalist School focuses on the economic viability requirement of the institution (Gonzalez-Vega 1993; De Briey 2005). This approach evaluates success by the institution's progress in achieving financial self-sufficiency. Donor agencies emphasize that MFIs must be self-sufficient in generating income from the loan portfolio to cover the cost of lending money and reduce dependence on external subsidies. This may hinder the goal of minimizing poverty, as it would make MFIs profit driven. The researchers have called this dilemma the "dual mission", which emphasizes the financial sustainability of the MFI in addition to the social outreach, although this is a matter of debate, and it is not yet clear that MFIs can achieve both objectives at the same time (Gutiérrez-Nieto et al. al. 2007; Abate et al. 2014; Mia and Chandran 2016). Cull and Morduch (2007) argue that MFIs could maintain profitability and social outreach simultaneously if they do not offer credit to a totally poor person. Paxton (2003) rejects that there can be a trade-off between financial sustainability and social outreach.

Nowadays, the participation of women in the workforce is an economic and social imperative. Unless women and girls are liberated from poverty, it is impossible to achieve peace, security, and sustainable development (Ban, 2010). Therefore, the sustainability of MFIs risks being undermined if women are not included in the board, especially as women are the main users of microfinance products and services. The behavioral economics literature shows that economic behavior differs according to gender (Hartarska et al., 2014). Regarding the role of women in microfinance, Batool (2015), suggested that there is greater acceptance towards female managers compare to the past. Moreover, Abdullah and Quayes (2016) indicate that most microcredit borrowers are women, and the prevalence of female borrowers is even greater among the very poor. Adusei et al. (2018) found that board gender diversity is a significant driver of MFI's capital structure and reduce their exposure to bankruptcy risk.

Since MFIs are hybrid organizations with the dual mission of financial sustainability and social purpose, the main goal of this paper is to predict the risk adjusted financial performance for MFIs, proxied by the ratio return on assets divided by portfolio at risk of more than 30 days (hereafter, ROA/PaR30). For this purpose, we apply the random forest (RF) algorithm to a sample of 30 microfinance institutions (MFIs) in Bangladesh from 2011 to 2018. Moreover, we introduce in our model four female variables such as female board members, female managers, female loan officers and female borrowers to assess the potential impact of such gender variables in the risk-adjusted performance.

The paper is structured as follows: in section 2 and 3, we show the general literature review and the literature of microfinance in Bangladesh; in section 4, we describe the design of our analysis; in section 5 we present the main results and findings; and in section 6 we summarize some main conclusions.

2. LITERATURE REVIEW

In terms of MFIs performance, Hartarska (2005) shows that the regulated MFIs provide lower ROA in Eastern Europe and Central Asia, finding no significant evidence that the breadth of outreach is affected by regulations. In addition, Hartarska and Nadolnyak (2007) highlight that the regulations have no impact on the MFI financial performance, finding little evidence that regulated MFIs typically serve fewer poor borrowers. On the other hand, according to Green (2020), the role of regulatory organizations is critical to combat Cambodia's debt overhang.

According to Yunus (2007), the use of consumer protection law and disclosure practices, such as those generally used by the banking sector, help the lender to disclose loan information that allows for comparability and interest rate effectiveness. This is a way to make customers aware of the agreements and avoids exploitation. In addition, truthfulness and disclosure practices in a competitive scenario are much more effective in lowering interest rates than interest rate ceilings. Therefore, before going to regulate interest rates, the government must necessarily make sure that it has the means to ensure that this provision is respected by all related parties. A regulation of interest rates must consider the facets that ensure transparency (Cotler 2010). One of the studies by Hartarska et al. (2009) takes data for Eastern Europe and Central Asia from the Micro Banking Bulletin and describes the size of MFIs. They found that MFIs with higher total assets experience a decrease in their costs, indicating the benefits of scaling up. Mersland and Strøm (2010) found no substantial sign of mission drift and conclude that, although MFIs earn higher profits with larger loan size, this allows them to continue to target poor clients. Thus, the cost-benefit comparison allowed MFIs to stay on track by serving typically poor clients rather than targeting wealthier clients.

More specifically, there are several studies on the financial performance of MFIs. Cull et al. (2007) examine profitability and patterns of loan repayment and cost reduction on 124 MFIs in 49 countries. Their results show the possibility of making profits while helping the poorest, although there is a clear trade-off in this regard. Mersland and Strøm (2009) explore the relationship between firm performance and corporate governance of MFIs using a global data set of MFIs. The results show that performance improves with local directors more than with international directors, and with internal auditors and female CEOs. Mersland et al. (2011) find that MFI internationalization improves social performance but does not improve financial performance. Tchakoute (2011) investigates the relationship between the status of MFIs and their performance and shows that the performance of private firms is better than that of NGOs. Esubalew et al. (2013) examine the effect of competition among MFIs. Their results show a negative relationship between intense competition and MFI performance. Janda et al. (2013) indicate that MFIs should have women as clients. Microfinance offers an opportunity for empowerment. In addition, women are more reliable than men for loan repayment, so portfolio at risk (PaR) is reduced.

As a result of the inability of traditional and development banks to productively finance the low-income population, microfinance appears to be a continuum between the economies of socialism and pure capitalism (World Bank, 2008). In general, the poor are unable to obtain money from formal money providers. This is the main cause of the lack of access to credit that leads to persistent poverty traps and income inequality (Beck et al. 2007; World Bank, 2008).

Based on the institutionalist school, one of the most recent studies is by Kharti (2014), who studies the determinants of the financial performance of 10 MFIs in Morocco during the period 2003-2010, finding that portfolio risk and MFI age are the key factors. They also find a significant impact of MFI solvency, staff productivity, and the number of female clients in the MFI financial sector. MFI financial performance is defined as the ability to cover its financial and operating costs. Ahlin et al. (2011), studied how the success of MFIs depends on macroeconomic features. The results showed the existence of complementarity between MFI performance and the broader economy. Dissanayake (2012) analyzed 11 MFIs in Sri Lanka, from 2005 to 2010, finding that the cost per borrower is a key determinant of return on equity and operational self-sufficiency. In addition, the operating expense ratio and depreciation ratio are determinants of return on equity (ROE), return on assets (ROA) and profit margin.

On the other hand, Quayes (2012) highlighted a positive complementary relationship between financial sustainability and depth of outreach showed that outreach to the poor can boost financial performance. Hermes and Hudon (2018) pointed out that the most important determinants are based on MFI characteristics like size, age, and type of organization as well as the MFIs’ external context such as macroeconomic, institutional, and political conditions. Pietrapiana et al. (2021) conducted a study on Peruvian MFIs where they analyzed the main factors that explain profitability, applying data mining techniques and finding relevant variables such as efficiency.

According to Gudjonsson et al. (2020), female managers and female loan officers improve financial performance in microfinance while female board members does not.

The main clientele of MFIs are females. Hartarska et al. (2014) revealed in their study that loans authorized by female loan officers have lower default rates. Following Díaz-Martín et al. (2021), female borrowers are the third predictor of MFIs' return on assets (ROA) in a sample of Argentine microfinance institutions.

According to Mia et al. (2021), from institution's perspective, the female workforce is based on female board members, female managers, and female loan officers, while the client's perspective is only based on female borrowers. Each hierarchical level has an important role in the success of MFIs. In their study, they concluded that female board members and female borrowers have a positive relationship with the financial performance of MFIs.

3. MICROFINANCE IN BANGLADESH

The beginning of microcredit was in Bangladesh. When Bangladesh became independent from Pakistan, it became a country overwhelmed by poverty. In fact, Bangladesh is one of the most economically depressed countries in the world. During the late 1970s, when the "Jobra" experiment was underway under Professor M. Yunus, the "Dheki Rin Prokolpa" was initiated by the Bangladesh Bank in collaboration with the "Swanirvar Bangladesh", and several other pilot schemes were initiated by a handful of the NGOs which were active then. At that time, it was difficult to conceive that these initiatives would lead to a major microfinance movement, which would make Bangladesh known to the rest of the world. The Nobel laureate Professor Muhammad Yunus founded Grameen Bank in 1983 and by 2000, it had more than 12,000 employees and 1,175 branches. Yunus was a guarantor of the loans he granted to the poor he identified. Grameen Bank is therefore considered to be based on trust rather than collateral, thus moving away from the traditional commercial bank known until then. In the 1990s, the term microcredit was replaced by microfinance, referring to a broad range of financial services to the poor such as credit, savings, insurance, and pensions (Karim, 2011).

In 2006, Yunus legitimized the microfinance model as key to women's economic and social empowerment. Khandker (2005) found that access to microfinance contributes to poverty reduction, especially for female participants in a panel data from Bangladesh.

According to Ahmed (2009), the main objectives of the microfinance programs are to increase employment opportunities and to enhance income adequate to lift the poor above the poverty line on a sustainable basis. The Palli Karma Sahayak Foundation (PKSF) commissioned a survey (1997-2001) through the Bangladesh Institute of Development Studies (hereinafter, BIDS) covering 3,026 sample households from 91 villages. The survey concluded that microfinance helped participant households to earn about 8 percent higher income than that of the non-participants. The participant households are better able to ensure more employment on own farms due to their better access to the land rental market. The impact study shows that there is positive program placement effect on nutrition status. The BIDS study finds small positive influence of participation on waste disposal and use of sanitary toilets among the land-poor households with no clear evidence of program impact on hand washing. The use of pure drinking water from hand tube well was found universal. Adult literacy rate is significantly higher among the eligible participants. The BIDS study also found that program participation increases the chance of both boys and girls to be enrolled in schools. Moreover, microfinance programs in Bangladesh have also increased women's participation in the activities of local government. Now women microfinance clients take greater roles in community activities for social change. About half of the Bangladeshi population lives below the poverty line with 80 percent in the rural areas, and the burden of poverty falls disproportionately on women. The total coverage of microfinance programs in Bangladesh is approximately 13 million households. Of the various employment activities (mainly self-employment), small-scale business/trade is the most important, accounting for more than 40 percent of fund disbursed by the MFIs. On the other hand, agriculture, food processing, transport, housing, and livestock sectors were getting relatively small portions of fund (Ahmed, 2009). According to Karim (2011), the microfinance gives poor women the resources to invest in their communities, families, and children’s lives, in fact, the poor women of Bangladesh have shown a great remarkable entrepreneurship and paid their loans at an astonishing rate of 98 percent. As of February 2004, PKSF has disbursed a total amount of about US$276.87 million among 4.55 million poor borrowers of which about 90 percent are women (Ahmed, 2009). The basic operational strategies of PKSF are the following:

- It does not directly lend money to the landless and the “assetless” people rather reaches its target groups through its partner organizations (POs).
- It provides greater thrust to institutional development, both its own capacity as an apex organization as well as the capacities of POs.
- It favors no model; instead, innovations and different approaches based on experience are encouraged.
- It acts as an advocate for appropriate policies and regulations useful for the microfinance sector.

Independent evaluation studies have shown that PKSF's microfinance program implemented through its POs has helped alleviation of poverty in Bangladesh.

Habib et al. (2015) concluded that the members of MFIs in Bangladesh are economically better in aspects like income, savings, housing quality, assets owned and the frequency of food intake.

Mia et al. (2017) found that in the saturation phase (2006-2015) based on the life cycle theory in the microfinance sector in Bangladesh, there was an increasing presence of uncoordinated microfinance institutions and expansion of multiple borrowing. On the other hand, Mia (2017) highlights that Bangladesh has made a big progress in her socioeconomic and economic development in the las few decades, and microfinance has placed significant contribution on this. However, we should consider other studies that highlight he emergence of systemic practices that jeopardize microfinance institutions' potential in Bangladesh to perform their social mission, according to Maitrot (2019).

In 2009, the Microfinance Information Exchange (MIX) released a Composite Ranking of the performance of microfinance institutions. The MIX Global 100 attempts to provide a composite picture of MFI performance using attributes like as outreach, efficiency, and transparency. High performing microfinance institutions seek to maximize performance in several areas such as improving outreach, minimizing risk, reducing cost, and strengthening returns. In the ranking of countries with most MFIs in Top 100, Bangladesh ranked fifth with five MFIs in top 100 of nine ranked MFIs. The table 1 shows the MFI Composite Ranking in top 100.

Table 1: MFI Composite Ranking

Country	MFIs in Top 100	All Ranked MFIs
India	20	51
Ecuador	9	44
Egypt	6	12
Philippines	6	34
Bangladesh	5	9
Cambodia	5	13
Bolivia	4	22
Bosnia and Herzegovina	4	13
Armenia	3	7
Mexico	3	27
Morocco	3	5
Dominican Republic	2	2
Jordan	2	6
Mongolia	2	4
Nepal	2	16
Peru	2	54
Serbia	2	4
Vietnam	2	5

Source: *MIX-Global-100-Composite*

The Composite Ranking included only MFIs that have demonstrated a commitment to maintaining financially sound operations and met minimum profitability requirements. To measure profitability, the ranking considered the returns of the last three years and looks for MFIs that have covered 100 percent of their costs at least once in that period. Specifically, the MFI Shakti Foundation of Bangladesh, ranked third in the world in terms of performance.

4. RESEARCH DESIGN AND METHODOLOGY

Our analysis is based on a sample of 30 Bangladeshi MFIs such as ASA Bangladesh, BASTOB, BDS, BEES, BRAC Bangladesh, BURO Bangladesh, CDIP, CTS, Coast Trust, ESDO, Ghashful, Gram Unnayan, IDF, Jagorani Chakra, NDP, NRDS, Nowabenki, POPI, Padakhep Manabik, RDRS, RRF, SDC, SKS Foundation, SOJAG, Sajida, Shakti Foundation, Society for Social Services, TMSS Micro Credit, UDDIPAN and Wave. Data has been extracted from the Microfinance Information Exchange (MIX) database (www.mixmarket.org) for the period 2011to 2018. In Table 2 we describe the sample of MFIs, in terms of total assets, number of employees, and the averaged values of all the independent variables used in our analysis.

Table 2: Sample of Bangladeshi MFIs.

MFI Name	*SIZE Total Assets (in USD)*	*Number of employees*	*Female board members (%)*	*Female managers (%)*	*Female loan officers (%)*	*Female borrowers (%)*	*Efficiency (%)*	*Solvency (%)*	*Productivity*	*Social performance (%)*
ASA Bangladesh	*1.583,368,594*	*12142*	*42.89*	*4.89*	*13.25*	*89.72*	*9.36*	*57.60*	*224.50*	*22.18*
BASTOB	*6,926,292*	*191*	*32.65*	*1.70*	*13.10*	*93.30*	*14.16*	*10.22*	*113.71*	*39.35*
BDS	*3,241,640*	*57*	*52.38*	*0.00*	*6.21*	*62.07*	*14.52*	*1.18*	*110.50*	*21.59*
BEES	*40,647,319*	*827*	*39.88*	*2.20*	*7.65*	*93.86*	*14.18*	*10.39*	*136.88*	*23.37*
BRAC Bangladesh	*1.690,116,144*	*2203*	*45.29*	*8.61*	*19.93*	*90.10*	*12.34*	*28.75*	*250.71*	*27.47*
BURO Bangladesh	*271,324,770*	*5309*	*19.05*	*7.86*	*22.69*	*89.86*	*11.07*	*15.13*	*147.13*	*27.43*
CDIP	*44,087,497*	*427*	*22.22*	*0.00*	*0.36*	*94.77*	*10.64*	*31.68*	*120.71*	*30.51*
CTS	*1,409,290*	*71*	*25.39*	*1.43*	*73.26*	*89.77*	*20.50*	*23.19*	*201.00*	*8.18*
Coast Trust	*14,649,652*	*331*	*41.12*	*16.67*	*48.45*	*97.45*	*14.15*	*9.28*	*142.75*	*19.42*
ESDO	*24,230,015*	*184*	*50.00*	*2.77*	*26.34*	*94.25*	*12.36*	*15.30*	*118.00*	*26.81*

Ghashful	*11,186,731*	*384*	*50.00*	*25.32*	*47.44*	*96.03*	*17.45*	*12.09*	*106.50*	*20.78*
Gram Unnayan	*32,569,610*	*927*	*22.86*	*1.25*	*11.45*	*91.57*	*11.60*	*24.22*	*124.00*	*23.71*
IDF	*19,049,551*	*218*	*22.15*	*4.37*	*30.83*	*98.91*	*14.71*	*19.68*	*148.50*	*20.06*
Jagorani Chakra	*118,264,467*	*2072*	*26.53*	*0.21*	*5.05*	*81.49*	*10.30*	*20.49*	*129.63*	*32.95*
NDP	*18,498,914*	*229*	*50.00*	*1.67*	*37.90*	*98.08*	*10.56*	*33.77*	*219.25*	*18.59*
NRDS	*7,191,946*	*228*	*28.57*	*0.74*	*39.48*	*100.00*	*14.79*	*21.72*	*151.20*	*16.93*
Nowabenki	*11,685,446*	*144*	*24.76*	*7.93*	*33.79*	*93.01*	*13.27*	*10.25*	*148.80*	*22.50*
POPI	*32,953,482*	*1012*	*31.97*	*13.19*	*25.12*	*99.23*	*14.35*	*10.77*	*116.14*	*21.73*
Padakhep Manabik	*80,443,033*	*1587*	*15.83*	*1.52*	*10.14*	*70.59*	*13.08*	*5.86*	*119.29*	*24.53*
RDRS	*45,744,076*	*1197*	*64.36*	*9.32*	*23.93*	*86.91*	*13.08*	*35.00*	*138.75*	*17.12*
RRF	*34,676,164*	*815*	*39.88*	*0.00*	*31.55*	*97.56*	*12.14*	*12.84*	*135.75*	*22.75*
SDC	*14,904,209*	*303*	*25.13*	*3.83*	*44.88*	*93.50*	*10.95*	*31.43*	*151.25*	*21.66*
SKS Foundation	*21,433,770*	*621*	*34.16*	*8.52*	*16.81*	*97.91*	*17.70*	*11.16*	*132.50*	*18.13*
SOJAG	*17,134,861*	*338*	*25.43*	*5.00*	*7.78*	*24.05*	*11.14*	*10.50*	*51.00*	*66.97*
Sajida	*58,891,971*	*893*	*39.03*	*7.24*	*17.05*	*91.89*	*13.08*	*16.11*	*117.00*	*34.51*
Shakti Foundation	*59,446,039*	*1164*	*49.90*	*17.15*	*19.86*	*85.33*	*13.93*	*15.97*	*176.13*	*13.77*
Society for Social Services	*129,628,568*	*2706*	*20.38*	*2.09*	*21.46*	*97.22*	*13.62*	*21.17*	*122.75*	*29.13*
TMSS Micro Credit	*178,552,341*	*2786*	*81.93*	*15.57*	*33.42*	*97.25*	*11.87*	*24.65*	*140.88*	*24.15*
UDDIPAN	*80,754,842*	*606*	*26.19*	*1.94*	*24.15*	*89.86*	*13.58*	*12.94*	*114.00*	*25.23*
Wave	*24,513,776*	*460*	*26.98*	*3.59*	*27.09*	*98.66*	*14.99*	*12.74*	*138.00*	*19.47*

Source: *Microfinance Information Exchange (MIX) database.*

In our study, we propose a new proxy for the risk-adjusted performance as the dependent variable. It is calculated by dividing the return on asset (ROA) by the portfolio at risk of more than 30 days (PaR30). ROA is a common indicator of financial performance which reflects the profit margin, as well as the efficiency of the institution (Bruett, 2005; Hartarska, 2005; Lafourcade et al., 2005; Mersland & Øystein Strøm, 2009, Im & Sun, 2015). According to Lam et al (2020), ROA is a better measure of the MFI financial performance than return on equity (ROE). In fact, the value of ROE can be misleading: a positive return on equity may or may not necessarily imply high financial performance of the MFI in the case where the MFI has both negative income and a negative book value of equity, possibly due to years of repeated losses resulting in negative retained earnings.

For the other hand, the portfolio at risk (PaR) is a proxy for the loan portfolio quality. The portfolio at risk of more than 30 days (hereafter, PaR30) represents the percentage of the total loan portfolio that has at least one payment more than 30 days overdue. It should be recalled that MFI operations are characterized by the logic of revolving credits, i. e., loanable funds are almost entirely repaid through credits. Collective loans with joint and several guarantees are often used as a mechanism to minimize the risk of failure, improve the performance of MFI portfolios, and achieve financial viability (Pitt and Khandker 1998; Ghatak 1999; Armendariz de Aghion and Morduch 2000; Cull et al. 2007).

Since MFIs should be sustainable in the long term, the ratio ROA/PaR30 proposed is interesting to be explored. In our model, we selected 9 main independent variables to assess their impact on the risk-adjusted financial performance, proxied by the ratio ROA/PaR30 as the dependent variable. We included the following four gender variables apart from other relevant ones from the existing literature:

Female board members

According to Galbreath (2011), women on boards and economic growth, in terms on ROE (return on equity), ROA (return on assets) and book-to-market value of equity, are a positive link in a sample of publicly listed firms from Australia. Moreover, Adams and Ferreira (2009) showed that female directors have a significant impact on board inputs and firm outcomes in a sample of US firms, where female directors have better attendance records tan male directors. In the same line, Erhardt et al. (2003) pointed out a positively association between board diversity and financial indicator of 127 large US companies' performance.

Female managers

The role of female manager also has relevance in financial performance along the years. Based on Kalleberg and Leicht (1991), businesses headed by women were nor more likely to go out of business, nor less successful, than those owned by men, based on 411 companies in South Central Indiana. Watson and Robinson (2003) found that although profits are significantly higher for male-controlled small and medium enterprises, when risk is considered, there was no significant differences between the performance of male and female managers. One step forward, Mersland and Strø (2009) found that financial performance improves with local rather than international directors, an internal board auditor, and a female CEO. Strøm et al. (2014) confirmed the positive relationship of female managers and the financial performance of 329 MFIs in 73 countries.

Female loan officers

Beck et al. (2013), interpreted in their study suggestive evidence for female loan officers' better capacity to build trust relationships with borrowers, so, loans monitored by female loan officers have a lower likelihood to turn problematic than loans handled by male loan officers. However, Van den Berg et al. (2015) found that male loan officers are better able to induce borrowers to repay than female loan officers, and it plays a crucial role in improving repayment rates.

Female borrowers

According to D'Espallier et al. (2011) women are generally better credit scored in microfinance than men, based in a data set of 350 MFIs in 70 countries. In fact, Grameen Bank switched its focus to female clients after experiencing repayment problems on the part of male borrowers in its early years (see Armendáriz and Morduch, 2005).

Particularly, in Bangladesh, the existing literature show that women are favored as borrowers due to their 97% recovery rate, compared to 89% for men, (Khandker et al., 1995). In the same line, Sharma and Zeller (1997) concluded that repayment rates can be good in credit groups with higher percentages of women. Some of these results can be explained by observing things from the women borrowers' perspective. Women, especially those in poor countries, have very limited mobility as compared to men (Armendáriz and Morduch, 2005). This is because women usually experience greater social pressure to take care of their children and are therefore more inclined to stay where they are. By having less mobility and lacking the financial capacity to relocate, women are often trapped in a place where the pressure and humiliation are higher if they do not repay their loans (Kutsoati and Morck, 2014). That is why it is expected that higher women's participation will result in higher repayment rates and hence better MFI financial performance.

Size

There is a direct relationship between MFI size, measured by normalized total assets, and its profitability (Cull et al., 2007; Demirguc-Kunt & Huizinga, 1999; Huq et al., 2017).

Efficiency

The measure of MFI efficiency is mainly determined by operating expenses relative to the loan portfolio (Microrate and BID 2003; Dissanayake & Anuranga, 2012; Rai & Rai, 2012). Edwards et al. (2009) highlight a positive relationship between financial performance and efficiency. Those MFIs that efficiently manage their operating expenses are profitable (Muriu, 2011), earning profits due to low operating expenses (Gudeta, 2013).

Solvency

The equity-to-assets ratio is the value of the MFI's equity divided by the value of its assets. It represents the amount of capital needed to cover additional unexpected losses in order to absorb potential shocks. (Online Accounting 2009; Michigan State University 2011). Rai and Rai (2012) found that the ratio of capital to asset was one of the key factors in the financial sustainability of MFIs.

Productivity

MFIs should adopt practices by focusing more on the client relationship to increase their performance management (Churchill, 2000; Norell, 2001; Schreiner, 2003). The productivity ratio is measured by the number of active borrowers compared to the number of loan officers or staff (Ayayi & Sene, 2010). This ratio works with the following logic: the higher the ratio, the more productive the MFI.

Social performance

In our model, we calculate average outstanding loan size normalized by GDP per capita as an inverse measure of social performance; in other words, the inverse of how much "good" the MFI is doing (Schreiner, 2003; Tchakoute-Tchuigoua, 2010). According to Lam et al. (2019), the average size of outstanding loan reveals the poverty status of MFI clients, as the "richer" poor tend to receive larger loans than the "poorer" poor. Consequently, larger loan sizes suggest that the MFI is serving the "richer" poor, thus doing less good socially.

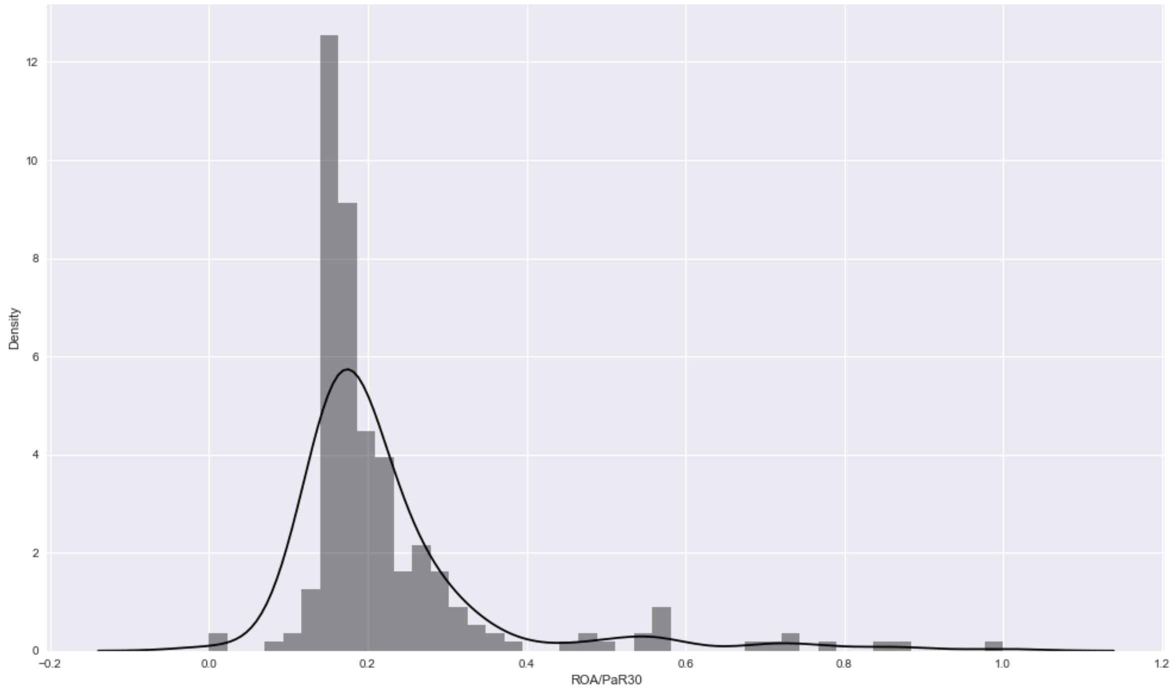
In Table 3, we summarize the description of the variables selected in our model, and in the figure 1, we plot the distribution of the data sample.

Table 3: Description of variables.

Dependent variable	
Risk-adjusted performance (ROA/PaR30)	*Return on asset ratio (net operating income / total assets) divided by Portfolio at risk > 30 days (outsanding balance on arrears over 30 days + total gross outsanding refinanced (portfolio) / total gross portfolio)*
Independent variables	
Female board members	*Percent of female board members = Number of board members who are women divided by the total number of board member in the MFI*
Female managers	*Percent of female managers = Number of managers who are women divided by the total number of managers in the MFI*
Female loan officers	*Percent of female loan officers = Number of loan officers who are women divided by the total number of loan officers in the MFI*
Female borrowers	*Percent of female borrowers = Number of active borrowers who are women divided by the total number of active borrowers*
Size	*Total net assets in the year (in USD)*
Efficiency	*Percent of operating expenses = Operating expenses divided by loan portfolio*
Solvency	*Equity to asset ratio = Total equity divided by total assets*
Productivity	*Productivity ratio = Number of active borrowers divided by total number of staff*
Social performance	*Average loan size divided by Blangladeshi GDP per capita*

Source: *Self-elaboration.*

Figure 1: Distribution of our data



Source: *Self-elaboration*

Since our sample contained some empty data, we had to fill the gaps by applying Multivariate Imputation by Chained Equations (MICE). To cope with the problems posed by the complexity of the data, it is convenient to specify the imputation model separately for each column of data. Given an empty data set in a random sample Y, the MICE algorithm obtains the distribution of the empty data set by iterating over the sample from conditional distributions of the form:

$$P(Y_1|Y_{-1}, \theta_1) \dots P\left(Y_p\middle|Y_{-p}, \theta_p\right)$$

Starting from a simple observed marginal distribution, the t-iteration of the chained equations gives us a sampling as follows:

$$Y_p^{*(t)} \sim P(Y_p|Y_p^{obs}, Y_1^{(t)}, \dots, Y_p^{(t)}, \theta_p^{*(t)})$$

where, $Y_j^{(t)} = (Y_j^{obs}, Y_j^{*(t)})$ is the imputed j-variable at t-iteration The number of iterations can be small; 30 in our case. The name chained equations refers to the fact that the MICE algorithm can be easily implemented as a concatenation of univariate procedures to complete the data. The algorithm runs m-flows in parallel, each of which generates a set of imputed data (Van Buuren & Groothuis-Oudshoorn, 2011).
In this work, we have established 21 MFIs as the training set, and 9 MFIs as the test set. Based on these assumptions, a model of MFI's financial performance can be estimated with the following specification:

$$\text{ROA/PaR30}_{it} = f\,(\text{FEMALE\_BOARD\_MEMBERS}_{it} + \text{FEMALE\_MANAGERS}_{it} + \text{FEMALE\_LOAN\_OFFICERS}_{it} + \text{FEMALE\_BORROWERS}_{it} + \text{SIZE}_{it} + \text{EFFICIENCY}_{it} + \text{SOLVENCY}_{it} + \text{PRODUCTIVITY}_{it} + \text{SOCIAL\_PERFORMANCE}_{it})$$

where,
i = 1,…; N for each MFIs
t = 1,…; T refers to the time period

As for the methodology, we are going to compare two main algorithms which are normally used in regression problems.

4.1 Random Forest Algorithm

We first use an ensemble-based technique which is the Random Forest –RF– algorithm. Combining a certain number of trees, the final prediction for the dependent variable (ROA/PaR30) is obtained as the average of the predictions of the individual trees that form the ensemble. Breiman (2001) defines RF as a combination of tree predictors such that each tree depends on the values of a random vector sampled independently and with the same distribution for all trees in the forest. The Random Forest algorithm, commonly used for both classification and regression, performs particularly well for high dimensionality data. It is a combination of decision trees in which one looks at which variable can predict a given target variable. The model algorithm bootstraps on the original data set. For each random sample of the original data, a classification tree model is fit, and a prediction is made for each tree by traversing to its leaf node. The RF-based methodology is considered one of the most accurate learning algorithms, as it offers some advantages: it runs efficiently on large databases, it can handle thousands of input variables without variable elimination, it provides estimates of which variables are important in classification, it works well with mixed numerical and categorical data, it makes no strong assumptions about the scale and normality of the incoming data that advances the construction of the forest, and finally, it is inherently capable of handling missing data. The RF algorithm obtains a considerably higher accuracy prediction than the classification tree. As Jiang et al. (2018) and Malekipirbazari and Aksakalli (2015) demonstrate, Random Forest algorithm performs better than other traditional classification models.

To calibrate the robustness of the Random Forest algorithm we perform a back-test on a subset of data. With N being the number of MFIs being the predictive (or estimated) values of ROA/PaR30, y being the actual values of ROA/PaR30, $y_i - \hat{y}_i$ being the mean of each set; the Root Mean Absolute Error (MAE) is calculated as follows:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i|$$

4.2 Support Vector Regression Algorithm

Support Vector Regression –SVR– is also a powerful algorithm for solving regression problems, which has been widely applied in various fields such as finance, medicine, and engineering (Zhang et al., 2019; Li et al., 2020). SVR is a type of supervised learning algorithm that is based on the idea of support vector machines, which were first proposed by Vapnik in 1995. In SVR, the goal is to find a function that best approximates the data points, while trying to minimize the errors. The function is represented by a linear combination of kernel functions, which map the input data into a higher-dimensional space. One of the main advantages of SVR is its ability to handle non-linear and non-stationary data. According to Iskenderoglu et al. (2020), the optimization problem for SVR can be formulated as:

$$minimize\ \frac{1}{2}||w||^2 + C\frac{1}{n}\sum_{i=1}^{n}(\xi_i + \xi_i^*)$$

subject to

$$y_i - w^* x_i - b \leq \varepsilon + \xi_i$$

$$w^* x_i + b - y_i \leq \varepsilon + \xi_i^*$$

$$\xi_i\ and\ \xi_i^* \geq 0 for\ all\ i$$

where C denotes a constant value, which has an effect on the grade of penalty loss when an error occurs during the training and it takes a value bigger than zero. For this convex optimization problem to determine decision function, it is expected that most of the data are in the ε –tube, which is the area between $f(x) + \varepsilon$ and $f(x) - \varepsilon$. But, when a data pair (x_i, y_i) locates outside of this tube, the slack variables (ξ_i and ξ_i^*) are minimizing the objective function. Minimize the first term and the second term means minimizing learning machine confidence interval and the empirical risk, respectively. One of the advantages of SVR is that it is well-suited for handling non-linear data by using the kernel trick, which maps the data into a high-dimensional feature space where a linear boundary can be found.

5. RESULTS AND MAIN FINDINGS

According to Tukey (1977), Exploratory Data Analysis (EDA) is an essential step in any research analysis. The objective of EDA is to visualize and examine the data, beforehand. Table 4, that provides a summary of the main statistics (mean, standard deviation, median, minimum, maximum and percentiles 25th and 75th) of the selected variables for all the MFIs.

Table 4: Descriptive statistics.

Variables	*Mean*	*SD*	*Min*	*P25*	*Med*	*P75*	*Max*
Female board members	*38,10*	*64,10*	*-72,23*	*22,22*	*28,57*	*43,48*	*909,69*
Female managers	*4,50*	*14,62*	*-73,64*	*0,00*	*2,16*	*6,67*	*100,00*
Female loan officers	*25,67*	*20,27*	*-10,28*	*12,46*	*22,30*	*33,79*	*166,60*
Female borrowers	*97,42*	*117,91*	*-652,73*	*89,33*	*95,85*	*98,04*	*1475,70*
Size	*155,785,447*	*447,905,411*	*1,340,687*	*12,715,393*	*26,003,390*	*74,044,640*	*3.527,200,208*
Efficiency	*13,35*	*5,13*	*0,44*	*10,93*	*13,27*	*14,79*	*70,40*
Solvency	*18,77*	*12,18*	*-1,88*	*10,50*	*16,18*	*23,84*	*76,90*
Productivity	*141,23*	*44,06*	*41,00*	*117,00*	*135,00*	*151,20*	*327,00*
Social performance	*24,75*	*11,41*	*6,80*	*17,82*	*22,09*	*28,31*	*80,76*
ROA/PaR30	*1,92*	*3,51*	*-3,82*	*0,17*	*0,70*	*2,00*	*21,41*

Source: *Self-elaboration.*

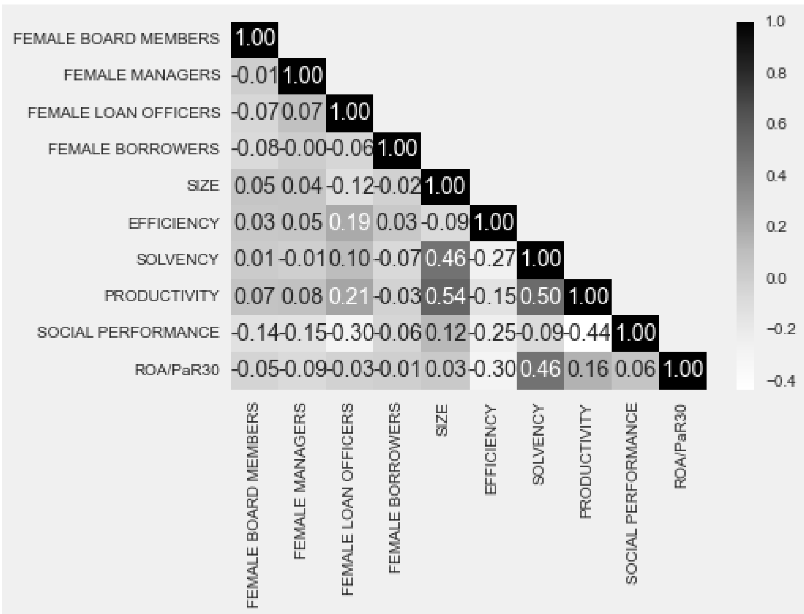
Churchill and Lacobucci (2005) stated that multicollinearity reduces the efficiency of the estimates, so we have tested for multicollinearity. In Table 5 and figure 2 we illustrate the mutual correlation coefficients for the dependent and explanatory variables in our analysis. According to Kennedy (2008) and Pal and Soriya (2012), correlations should exceed the cut-off value of 0.8 to detect collinearity between two variables. Since all the correlation coefficients in the correlation matrix are less than 0.8, there is no multicollinearity problem.

Table 5: Correlation matrix

	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
1. Female board members	1									
2. Female managers	-0.00833	1								
3. Female loan officers	-0.06515	0.074106	1							
4. Female borrowers	-0.08306	-0.00054	-0.05792	1						
5. Size	0.050064	0.040946	-0.12411	-0.02187	1					
6. Efficiency	0.031737	0.045684	0.186824	0.03042	-0.09325	1				
7. Solvency	0.013706	-0.01254	0.102068	-0.07369	0.464584	-0.27374	1			
8. Productivity	0.065895	0.077441	0.210865	-0.0316	0.544527	-0.1484	0.500969	1		
9. Social performance	-0.13541	-0.14905	-0.30321	-0.05618	0.121488	-0.24721	-0.09092	-0.43676	1	
10. ROA/PaR30	-0.04698	-0.08546	-0.03173	-0.01184	0.025409	-0.29691	0.461748	0.156531	0.062543	1

Source: Self-elaboration

Figure 2: Correlation matrix



Source: *Self-elaboration*

The table 6 shows some samples of test data and the ROA/PaR30 outputs experimental and RF/SVR prediction with respect to normalized test inputs.

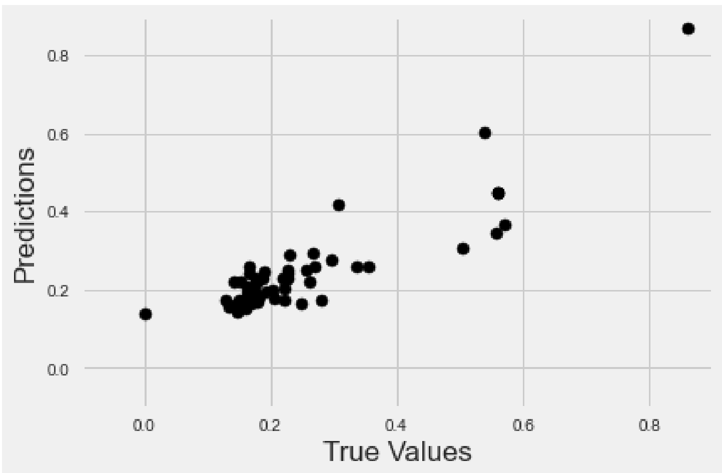
Table 6: ROA/PaR30 expected and RF/SVR prediction

Sample number	*Female board members*	*Female managers*	*Female loan officers*	*Female borrowers*	*Size*	*Efficiency*	*Solvency*	*Productivity*	*Social performance*	*Expected roa/par30*	*Estimated RF*	*Estimated SVR*
1	0.107499	0.424082	0.106888	0.351981	0.003224	0.259434	0.211359	0.353147	0.125203	0.148101	0.148885	0.206879
2	0.117205	0.450690	0.131030	0.349603	0.634908	0.102058	0.674952	0.776224	0.286101	0.270347	0.260842	0.252417
3	0.094093	0.390340	0.124928	0.355563	0.006081	0.095054	0.375114	0.311189	0.198350	0.228625	0.289730	0.448907
4	0.102651	0.424082	0.078789	0.343899	0.036057	0.155803	0.356200	0.342657	0.302461	0.187316	0.227830	0.454711
5	0.043852	0.423466	0.184830	0.347306	0.021084	0.123785	0.171880	0.374126	0.344240	0.202258	0.199467	0.225733

Source: Self-elaboration

The normal-predicted accuracy for Random Forest algorithm (MAE) is 79.64% as illustrated by the scatter plot of actual ROA/PaR30 vs predicted ROA/PaR30 (predictions) in figure 3.

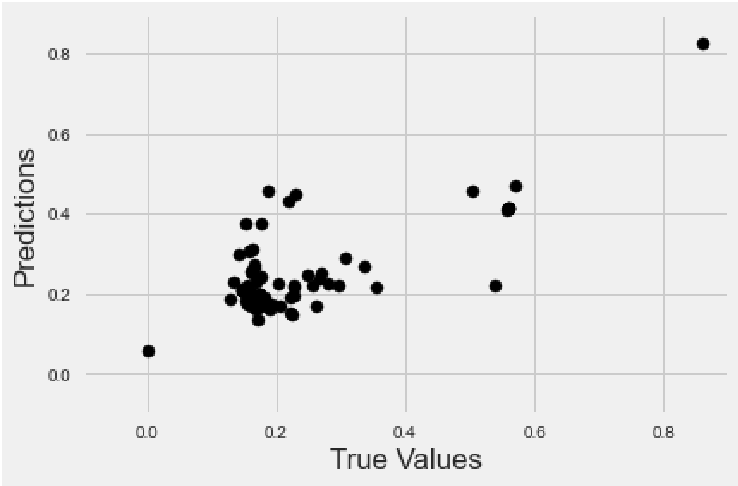
Figure 3: Scatter plot RF Algorithm



Source: *Self-elaboration*

On the other hand, the normal-predicted accuracy for Support Vector Regression algorithm (MAE) is 51,75% as illustrated by the figure 4 with the comparison between the true values of ROA/PaR30 vs the predicted ROA/PaR30.

Figure 4: Scatter plot SVR Algorithm



Source: *Self-elaboration*

The results of both algorithms are summarized in the table 7.

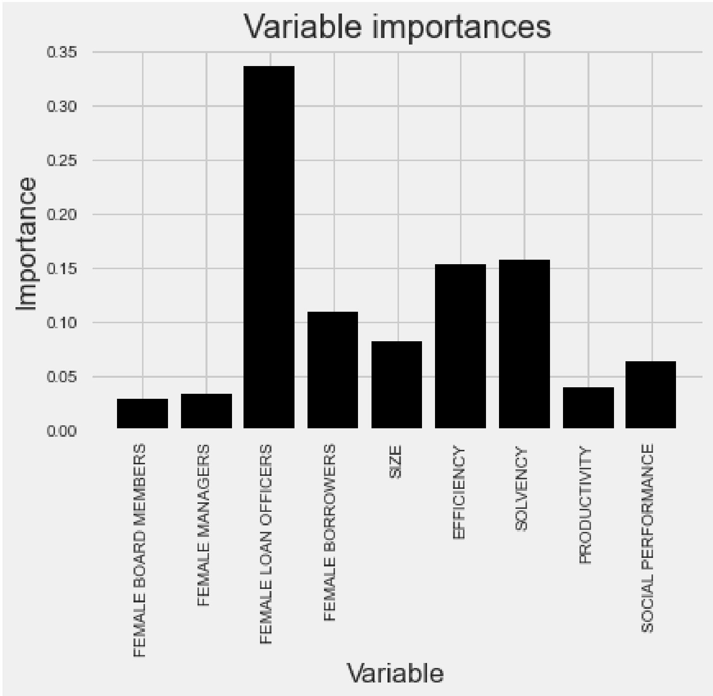
Table 7: Results of score and MAE for RF and SVR Algorithms

	Normal-predicted accuracy (R2)	*Mean Absolute Error (MAE)*
Random Forest	*79,64%*	*0,041*
Support Vector Regression	*51,75%*	*0,071*

Source: *Self-elaboration*

As table 7 illustrates, RF algorithm provides the best fit for our data. Accordingly, the figure 5 summarizes the key drivers of our dependent variable –risk-adjusted performance–.

Figure 5: Independent variables ordered by importance




```
Independent variable: FEMALE LOAN OFFICERS -> Importance: 0.34
Independent variable: SOLVENCY             -> Importance: 0.16
Independent variable: EFFICIENCY           -> Importance: 0.15
Independent variable: FEMALE BORROWERS     -> Importance: 0.11
Independent variable: SIZE                 -> Importance: 0.08
Independent variable: SOCIAL PERFORMANCE   -> Importance: 0.06
Independent variable: PRODUCTIVITY         -> Importance: 0.04
Independent variable: FEMALE BOARD MEMBERS -> Importance: 0.03
Independent variable: FEMALE MANAGERS      -> Importance: 0.03
```

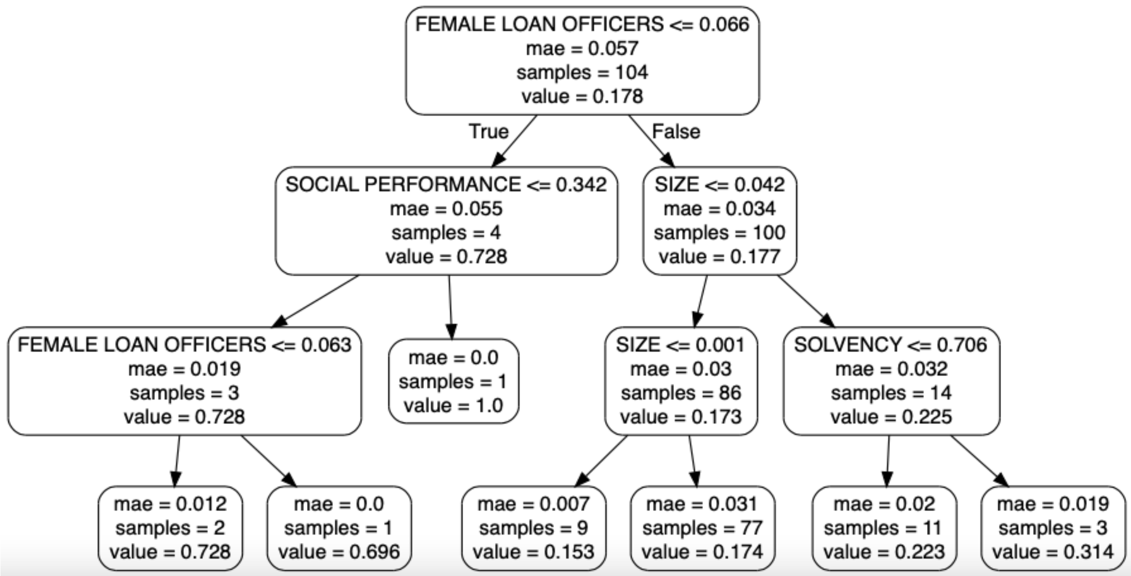
Source: *Self-elaboration*

As figure 5 illustrates, the female loan officers is the most important explanatory variable, followed by the solvency, the efficiency and the female borrowers, in this order, when predicting the MFI's risk-adjusted performance. Moreover, female board members and female managers are also significant but less than size, social performance and productivity.

The number of occurrences of a feature variable is proportional to the importance measure of a feature variable. This is because the algorithm selects the feature at any specific node position based on maximum information gain. The measure gives an indication of which observations are close to each other based on the class predictions made on the tree collection. Each random sample has a set of out-of-bag observations that are excluded due to random sampling. For each tree, predictions are made based on the out-of-bag observations.

In figure 6, we plot one of the decision trees obtained by RF, highlighting that the female loan officers is the most important variable, followed by the solvency, the efficiency and the female borrowers in the ROA/PaR30 prediction process.

Figure 6: Decision tree



Source: *Self-elaboration*

6. CONCLUSIONS

It is widely argued that the participation of women as borrowers can enhance financial performance as they are more conservative and disciplined when it comes to repaying instalments, less likely to move, and face more social pressure than their male counterparts. Moreover, previous studies find that women, working in different positions within MFIs, are better skilled, are inclined to establish trust-based employee-client relationship and are prudent in nature, thus helping to provide better firm performance. The aim of this paper is to deepen the analysis of the main gender drivers –Female board members, Female managers, Female loan officers, and Female borrowers– influencing the risk-adjusted performance –proxied by the ratio ROA/PaR30–, instead of using the traditional non-adjusted financial performance –ROA– as the dependent variable. Since MFIs are hybrid organizations with the dual mission of financial sustainability and the social purpose of poverty alleviation, we propose the use of such risk-adjusted measure of the financial performance as a crucial variable to ensure the survival of the MFIs in the long term.

By running the RF algorithm, we find that the female loan officers are the most important variable in predicting the risk-adjusted financial performance of Bangladeshi MFIs, being assigned 34% relative importance. It is followed by the solvency, measured by the equity to assets ratio, the efficiency, measured by operating expenses relative to the loan portfolio and the female borrowers, in this order. Moreover, female board members and female managers are also significant but less than size, social performance, and productivity. As included in the 2030 Agenda, the Sustainable Development Goal –SGD–8 seeks to promote sustained, inclusive, and sustainable economic growth; SGD 10 aims to reduce inequality within and between countries and SGD 5 aims to promote gender equality. MFIs are proved to be an effective mechanism to fulfil such strategic goals but also the long-term sustainability and survival of MFIs is contingent on gender variables. Particularly, by increasing the main gender driver –percent of female loan officers–, apart from promoting gender equality within the MFI –in line with SGD5–, we are also contributing to improve the MFIs risk-adjusted performance. Our paper reinforces the idea of gender solidarity; that is, the female loan officers are more likely to serve female borrowers, who are more cautious, risk-adverse, and reliable than men in repaying loans, thus reducing the portfolio at risk, resulting in a positive a self-reinforcing loop.

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CAPÍTULO 5: CONCLUSIONES

5. CONCLUSIONES

A continuación, se muestran las conclusiones de cada artículo y, finalmente, unas conclusiones generales.

5.1. CONCLUSIONES DEL ARTÍCULO: ARE MICROFINANCE INSTITUTIONS' FINANCIAL PERFORMANCE GENDER DRIVEN? EVIDENCE FROM ARGENTINA

En este artículo, investigamos los determinantes del desempeño financiero en una muestra de 18 IMFs en Argentina para el período 2002 al 2018. Al aproximar esta variable a través del ROA, aplicamos una técnica de minería de datos; en particular, el algoritmo Random Forest (RF), para predecir tal variable dependiente, obteniendo un 93,3% de precisión en la validación cruzada.

Encontramos que la calidad de la cartera de crédito (PaR30) es la variable más importante en la predicción del ROA, asignándole una importancia relativa del 48%. La eficiencia, medida por los gastos operativos relativos a la cartera de crédito, es la segunda variable más importante, con un 21% de importancia relativa. Además, contribuimos al debate existente en la literatura en la medida en que la variable social medida por el número de prestatarios activos que son mujeres dividido por el número de prestatarios activos en el año se considera el tercer predictor relevante del ROA, obteniendo una significancia del 17%; en otras palabras, el género se muestra como uno de los principales impulsores del desempeño financiero de las IMFs argentinas. Además, las mujeres son más confiables que los hombres en el pago de los préstamos, lo que reduce el riesgo de la cartera y, en consecuencia, mejora el desempeño financiero de las IMFs en términos de ROA. En cuanto a la solvencia y la productividad, reciben una importancia relativa del 8% y el 3%, respectivamente, mientras que la productividad y el tamaño alcanzan el 2%. Finalmente, el desempeño social tiene una importancia relativa del 1%, y, las variables macro y la crisis (variable *dummie*), no son relevantes en nuestro modelo.

Este documento tiene implicaciones gerenciales importantes para el fortalecimiento del sector microfinanciero argentino, ya que identifica las principales variables que inciden en el desempeño financiero. Al establecer umbrales estratégicos en dichas variables clave (PaR30, eficiencia y proporción de mujeres prestatarias), los gerentes de las IMFs pueden monitorizar y controlar convenientemente su gestión en aras de garantizar la sostenibilidad financiera a largo plazo de entidad, así como el equilibrio en su doble misión; social y económica.

5.2. CONCLUSIONES DEL ARTÍCULO: IS RISK-ADJUSTED FINANCIAL PERFORMANCE SENSITIVE TO GENDER? EVIDENCE FROM BANGLADESH MICROFINANCE INSTITUTIONS

En este artículo, investigamos las principales variables de género –mujeres prestatarias, mujeres directivas, mujeres gerentes y mujeres oficiales de crédito – que influyen en el desempeño financiero ajustado al riesgo. Para ello, utilizamos como proxy de dicha variable dependiente el ratio ROA/PaR30, para una muestra de 30 IMFs de Bangladesh, dentro del período comprendido entre 2011 y 2018.

Ejecutamos dos algoritmos para ver cuál resulta mejor predictor; en concreto aplicamos un SVR y un RF, obteniendo una mayor precisión en este último. Al ejecutar el algoritmo RF, encontramos que las mujeres oficiales de crédito constituyen la variable más importante para predecir el desempeño financiero ajustado al riesgo de las IMFs de Bangladesh, el cual recibe una importancia relativa del 34%. Le siguen la solvencia, medida por la relación patrimonio sobre activo, la eficiencia, medida por los gastos operativos relativos a la cartera de crédito y las mujeres prestatarias, en este orden. Además, las variables mujeres directivas y mujeres gerentes resultan ser también significativas, aunque en menor medida que el tamaño, el desempeño social y la productividad.

Al aumentar el porcentaje de mujeres oficiales de crédito, además de promover la igualdad de género dentro de la IMF –en línea con el Objetivo 5 de los ODS–, también estamos contribuyendo a mejorar el desempeño ajustado al riesgo de las IMFs. Nuestro artículo refuerza la idea de solidaridad de género, es decir, es más probable que las funcionarias de crédito atiendan a las prestatarias, que son más cautelosas, adversas al riesgo y confiables que los hombres en el pago de los préstamos, lo que reduce la cartera en riesgo, y lo que origina, como resultado, un bucle positivo que se refuerza a sí mismo.

5.3. REFLEXIÓN FINAL

Con este trabajo refrendamos la idea de que la participación de las mujeres como prestatarias puede mejorar el desempeño financiero, ya que son más conservadoras y disciplinadas, cuando se trata de pagar las cuotas, tienen menos propensión a la movilidad y soportan más presión social que sus contrapartes masculinas. Además, las mujeres, que trabajan en diferentes puestos dentro de las IMFs, suelen estar mejor capacitadas, tienden a establecer una relación empleado-cliente basada en la confianza y son de naturaleza prudente, lo que promueve un mejor desempeño financiero ajustado al riesgo de la empresa. Por tanto, las instituciones microfinancieras que persigan este compromiso social deberían focalizarse en el colectivo de mujeres como clientes y promover la igualdad de oportunidades en su estructura de interna ya que, al mismo tiempo, estarán garantizando su sostenibilidad financiera a largo plazo.

CAPÍTULO 6: REFERENCIAS

6. REFERENCIAS

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