MULTI-LEVEL MARKETING PARTICIPATION AND SOCIAL CONNECTIVITY

Research Challenge Technical Report

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Abstract

Anecdotal evidence suggests that involvement with direct-selling intermediaries may negatively affect household financial well-being. This is particularly relevant for Multi-Level Marketing (MLM) firms, where rosy marketing claims contrast with the negative financial experiences of many participants. By using county-level data on social network connectivity and demographic characteristics, we provide initial evidence on the determinants of MLM activity. Our results indicate that MLM participation is higher in middle-income areas and that connectivity is important for explaining MLM incidence. Our results highlight the need for more research into an increasingly important part of the US labor market and are particularly relevant given the increase in alternative working arrangements.

Keywords: Multi-level marketing; 'Gig'-economy; Social connectivity; Consumer financial protection; Entrepreneurship.

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1. Introduction

Over the past decade the share of employees with alternative work arrangements rose by more than 5 percentage points, primarily driven by an increase in independent contractors (Katz and Krueger, 2016). While this trend has been prominently discussed through the lens of the 'gig'-economy, where independent workers work on their own terms and sell directly to customers themselves, much of this work is facilitated via offline intermediaries (Katz and Krueger, 2016). In particular, a form of offline intermediary that has received limited attention are *direct selling* businesses, where individuals join as an independent contractor and sell goods provided by a parent company. More than 5 million Americans had a part or full-time involvement in a direct-selling business in 2016, corresponding to approximately 3 percent of the labor force. A further 15 million were directly affiliated, a number that grew 30 percent from 2011 to 2016 (Direct Selling Association, 2017a).[3]

Moreover, anecdotal evidence suggests that involvement with a direct-selling intermediary need not be strictly positive for participants' financial health. This is particularly relevant for so-called Multi-Level Marketing (MLM) firms, where the business model relies on individual retailers' commission-based product sales direct to customers and on the ability to recruit new members into the company. Most individuals who join an MLM do not experience any financial gains, in contrast to the often rosy marketing claims (FTC, 2016a). Considering the relatively large share of the labor force involved in direct selling and its growing importance, the academic attention on the direct-selling industry has been surprisingly limited.

The purpose of this study is to provide an initial examination of direct-selling firms, with a particular focus on understanding the drivers behind the choice to join a MLM. Specifically, we investigate the link between the incidence of MLM activity in a county and social networks, income, demographic characteristics, and social capital -- providing new insights into an increasingly important phenomenon in today's labor markets. By focusing specifically on MLM businesses we also shed light upon an important vulnerability in today's society, improving our understanding of why individuals invest in projects that regulators continue to warn consumers against.[4] As state, federal, and non-governmental organizations paint an increasingly precautionary view of the MLM industry, understanding the economic determinants and consequences of joining a MLM may have important policy and regulatory implications.

To date, there exists no empirical or theoretical literature about the type of individuals who join a MLM company. This is perhaps not surprising, as data about who participates, their motivations, their income and their expenses is difficult to obtain. Many of the firms involved are privately held and are reluctant to share data on their customers. We solve this issue by obtaining data from a Freedom of Information Act (FOIA) request to the Federal Trade Commission (FTC) on individuals exposed to a large MLM company. The FTC investigated and filed a lawsuit claiming that the company made misleading moneymaking claims and that it incentivized its distributors to recruit other members, rather than selling its own product – a violation of the FTC act designed to combat Ponzi schemes. The company's settlement was used to refund over $200 million

[3] Katz and Krueger (2016) report a slightly lower estimate for the number of individuals involved in direct selling ventures. They report that 19.4 percent of their sample is involved in direct selling in their job, and that 7 percent of these individuals report working through an intermediary. This corresponds to 1.5 percent of the labor force. Of those 1.5 percent, two thirds report working through an offline intermediary. Others have estimated a much larger fraction of the population, up to 30% are involved in 'independent work' (Oyer, 2016).

[4] The FTC warns: "Not all multi-level marketing plans are legitimate. If the money you make is based on the number of people you recruit and your sales to them...It could be a pyramid scheme."

dollars to nearly 350,000 independent individual distributors exposed between 2009 and 2015. Our data gives us geographic information on each one of the distributors as well as their personal settlement check – a rough proxy for the size of their losses.

We aggregate the individual-level data to the county-level and match this to data from several different sources. First, we obtain data on the Social Connectedness Index from Facebook, which allows us to measure the strength of social connections within and between counties across the United States. One of our primary hypotheses is that participation in a multi-level marketing business is driven partly by social behavior.

A MLM business by definition relies upon individual members to continuously recruit new members, often through networks of friends or family. The Direct Selling Association states that more than 70% of sales of all MLM businesses are through a direct person-to-person channel, while an additional twenty percent are facilitated by 'group sales' (Direct Selling Association, 2017a). Both of these channels increasingly rely on online social networks, where indeed a rising share of MLM sales are conducted. The New York Times noted in a recent article that while group or event-sales have existed since at least the 1940's, more modern distributors "...add a contemporary spin with the use of e-commerce, mobile credit card swipers, and heavy use of Facebook, YouTube and Twitter (Dunn, 2016).

Our results suggest that the overall connectivity of a county is an important correlate of MLM participation, primarily driven by connectivity within the same county. A county with more connections may have larger opportunities to profit from a MLM business, as the potential for retail sales and recruitment is larger. Moreover, we find that counties with MLM incidence are connected to other counties with high MLM incidence. However, it is unclear if individual's make this calculation when they are deciding on whether to join an MLM business, or that MLM businesses are more active in areas where social connectivity is high.

Moreover, the implication of social participation in MLM activity, and the associated negative experience, is a two-way street. On one hand, vulnerable households may be more easily recruited into participation if they are specifically targeted by individuals within their network. At the same time, awareness of the pitfalls and important educational and financial literacy programs designed to combat predatory business opportunities could be spread through social networks. If these types of opportunities are spread or exacerbated via social networks and social connectedness, it presents an actionable insight to mitigate the risk for vulnerable households in the future.

We find that MLM incidence is particularly concentrated in middle-income counties, and in counties with higher income inequality. Our preferred explanation is that joining a MLM requires a certain level of financial resources, which implies that lower-income counties are less able to participate.[5] We also find that areas with relatively more women outside the labor force compared to men had higher MLM incidence. This correspond to statistics reported by The Direct Selling Association (2017a), who report that 74 percent of individuals involved in a direct selling business was female. Furthermore, counties with higher entrepreneurial activity in general have higher MLM incidence, but not counties with more sole proprietors. In general these results hold when we focus only on communities with an above median concentration of Hispanic inhabitants. This suggest that MLM activity may be a substitute for women staying at home, but that it is not a substitute for other types of entrepreneurship.

The positive correlation between MLM incidence and county-income levels does not mean, however, that the losses experienced by an

[5] It is also possible that the way that the FTC distributed reimbursements unintentionally excluded low-income counties, as the minimum losses for receiving a check was $1,000.

individual through an MLM are trivial. In fact, we find that counties with higher income experienced larger losses from joining an MLM, as proxied by the size of the settlement check. As we do not have individual-level data, we are not able to determine how individual finances are affected by joining a MLM, nor whether the magnitude of the losses were small or large.

Reassuringly, we find that the demographics of our sample correspond to the statistics reported by the Direct Selling Association. In particular, we find that our measure of MLM incidence is correlated with county-level Hispanic share, counties with a larger female share, a larger fraction of females not participating in the labor force relative to men, and a younger age structure. The Direct Selling Association (2017a) reports that 22 percent of the individuals involved in direct selling were Hispanic compared to their 18 percent share of the US population, that 74 percent of individual involved in direct selling were females, and the age distribution of direct selling skews towards younger individuals. To the extent that we are able to measure it, these results suggest that that our results generalize to other firms in the industry. Given the nature of our data, however, we wish to clearly state that we do not mean to suggest that all MLM engage in questionable behavior.

Finally, we investigate where individual's lost the most by examining the size of their refunds. Our findings indicate that investment losses were more severe in counties with a higher share of Hispanics and women, women outside of the labor force relative to men, and counties with high income inequality and lower educational achievement.

Our research expands upon recent literature on the changing nature of employment in the United States (Katz and Krueger, 2016). We test a number of plausible mechanisms that help explain the sorting of individuals into these types of alternative business opportunities. Our findings therefore contribute to recent work by Katz and Krueger (2017) who investigate the influence of unemployment in the rise of alternative work, Cook et al. (2018), who consider the role of gender and particularly the gender earnings gap using data from Uber, and Chen et al. (2017) who, also using data from Uber, document the positive wage and earnings effect of flexible work. In addition, we connect to a growing literature on the financial vulnerability of households by providing demographic patterns of participation in a seemingly harmful investment. Similar to our paper, Leuz et al. (2017) find that a sizable number of investors participate in costly 'pump-and-dump' schemes and some actively seek out these types of investments. In contrast, they find that past behavior (e.g., investment decisions) may be better predictors of future activity than demographic characteristics. We also draw somewhat precautionary conclusions echoing Guran et al. (2015), who suggest that trust and shocks to trustworthiness are spread through closely-knit social networks, and Deason et al. (2015) who reiterate the importance of cultural affinity in propagation of previous fraudulent activities collected from the SEC.

2. Background

From 1995 to 2015 the share of workers in alternative work arrangements (temporary help agency workers, on-call workers, contract workers, and independent contractors or freelancers) rose from 10 percent to 15.8 percent (Katz and Krueger, 2016). The largest contributor to the increase was Independent Contractors, who find customers on their own to sell a product or service, which increased from 6.3 percent in 1995 to 9.6 percent in 2015.

Katz and Krueger (2016) specifically investigate the role of direct selling to customers in a survey in association with the RAND American Life Panel. They report that 19.4 percent of US employees respond that they are involved in direct selling on their job, and that 7 percent of respondents report using an intermediary, such as Avon or Uber, in their direct selling activity. This corresponds to 1.4 percent of the labor force being active in direct selling activities in 2015. Among those involved in direct selling through an intermediary two thirds reported using an offline intermediary and one third reported using an online intermediary.

This is comparable to the estimate from the Direct Selling Association (DSA), which report that 4.5 and 0.8 million individuals were "Part-Time Business Builders" and "Full-Time Business Builders" in 2016, respectively. The organization reports that 20.5 million individuals in total were involved in direct-selling in 2016, up from 15.6 million in 2011.[6] The organization states that direct selling activity is also over-represented among Americans with Hispanic ethnicity (22 percent compared to the 18 percent national average) and women (74 percent in 2016). DSA estimates that direct sales generated $35.84 billion of revenues in 2016 in the United States, mainly through person-to-person sales. Globally, Direct Selling News (2017) reports that total revenue for the top 100 direct selling firms exceeds $81 billion, with the top 10 companies accounting for $40.3 billion.

A specific form of direct-selling is through a Multi-Level Marketing (MLM) firm, which acts as an intermediary by supplying the products that an associated individual can sell. The business model for MLM firms rely on non-salaried sales force (*participants*) that act as independent contractors and generate revenue for the parent company. The participant are paid commissions, bonuses, discounts, dividends, and/or other forms of payment in return for selling products or recruiting members (Albaum and Peterson, 2011). The participants can purchase the company's products at a discount to retail price, either because they want to consume the products themselves or because they wish to sell the products onwards for a profit. Depending on the organization, these products may only be available in the market place through direct sales from a participant.

The participants are often prohibited from selling the products in a physical store, leaving direct sales within the social networks as the only viable option for generating revenues (Greve and Salaff, 2005). Additionally, the MLM company often regulates the price of the products to the end-user, but offers bulk-discounts to participants. This provides an incentive to order large amounts of products, as the per-unit price then decreases. Discounts based on order size becomes problematic, however, if the participant cannot sell their products and instead build up a stock of inventory (Federal Trade Commission, 2016a, p.19).

When the importance of direct sales is limited, the main revenue source instead becomes commission payments from recruitment of other participants. By recruiting new members, a participant can potentially generate "downstream" revenue not only from their direct recruits, but also from the recruits of their recruits. In other words, Participant A will receive commission payments based on the revenue of

[6] The majority of individuals (15.2 million in 2016) were involved as "Discount Customers." This activity does not necessarily involve any active promotion or sales.

their own recruit B, but also based on the sales of C and D, who were recruited by B. The revenue generated by B, C and D are referred to as "downstream" revenue for A. Note that these commission payments are not always dependent on profits, but can also be based on revenues (Federal Trade Commission, 2016a).

In general, the profitability of participating in a MLM company is debated. In a critique of the industry, Taylor (2011) report that 99.94 percent of participants in a MLM lose money, suggesting that the vast majority of independent retailers experience financial losses from joining a MLM. In contrast, Albaum and Peterson (2011) report results from research by the Direct Selling Association that show that the mean gross income is $14,500 and the median gross income is $2,500. More specifically, one MLM company stated that "nearly 86 percent of U.S. membership (466,926) did not receive any earnings" (Statement, 2016). The company states that many of these members join in order to receive a discount on the products. The company states that 14 percent of members in 2015 sponsored at least one person and earned commission payments based on the sales of the member(s) they sponsored. In addition to any retail profit, the top 50 percent made $245 in earnings, the top 10 percent made more than $4,350 in earnings, and the top 1 percent made more than $82,000 in earnings (Statement, 2016).[7]

The over-reliance on recruitment for producing revenues and exaggerated claims about potential profitability for the average participants has received criticism (Koehn, 2001) and indeed legal challenges from regulators. In a recent lawsuit against a large MLM company, the FTC alleged that the company had made unlawful claims about the likely income from pursing either full-time or part-time business opportunities as an independent retailer (Federal Trade Commission, 2016a). The claim against the company was that their compensation program incentivized recruitment of additional participants instead of retail sales, and that the products themselves were not sufficiently profitable. The FTC cite the companies own numbers as saying that sales to customers outside the company network accounts for 39 percent of product sales (Federal Trade Commission, 2016a, p.18), and claims that "the overwhelming majority of (MLM Company) Distributors who pursue the business opportunity make little or no money, and a substantial percentage lose money." The lawsuit was settled in 2016, with the company agreeing to pay $200 million and restructure their business. The FTC used the payment to refund nearly 350,000 people who lost money running a business (Federal Trade Commission, 2016b).

[7] Income and earnings from employment opportunities in the broader alternative and independent work space have also been noted to be volatile and even `unpredictable' according to survey participants (Oyer, 2016).

3. Data

3.1 Sources of data

Our main source of data comes from a Freedom of Information Act (FOIA) made to the Federal Trade Commission in 2017. As previously described, the FTC filed a lawsuit in 2016 claiming that a large United States-based MLM company had made misleading statements and marketing claims regarding the financial potential of joining the company as an independent retailer, and that the company's business model too strongly incentivized the recruitment of new members over direct product sales. The company settled its claims with the FTC and eventually refunded over $200 million to nearly 350,000 independent participants who lost money between 2009 and 2015 (Federal Trade Commission, 2016b). The FTC refunded participants who experienced losses above $1,000, `but got little or nothing back from the company'. According to the FTC the size of a check correspond to a "partial refund" of the losses the individual experienced.

The FOIA provides us with raw, redacted data on the geographic location for each participant, along with the size of their personal settlement check. We use the geographical location on the check to assign each individual to a county, and calculate a county-level MLM incidence as the number of checks divided by the population. We scale this value by 10,000 individuals for legibility. We also drop military, international, and non-continental US addresses.[8] Our unit of observation will therefore be the county, as we do not have more information about the individuals other than where they live and the size of their check.[9]

We combine the county-level MLM incidence with several other data sources. First, we use the Social Connectedness Index (SCI) from Bailey et al. (2017). This index is based on the number of friendship links on Facebook Inc., the social network platform. Given the near-ubiquitous coverage of Facebook for the US population, this data provides a detailed, comprehensive and representative measure of friendship on a national level Bailey et al. (2017). We use this data to better understand the social nature of MLMs. The index provides a measure of connectivity within a county, but also for each county-pair in the United States.[10]

Second, we collect data on income mobility, demographics, unemployment, income and income inequality. We use data on from the U.S. Census Bureau's 2006-2010 American Community Survey (ACS) for a county's population, median household income, and race, age, and gender, and educational composition. Unemployment statistics originate from the Bureau of Labor Statistics' (BLS) Local Area Unemployment Statistics (LAUS) and provide the unemployment rate by country from 1990 to 2017. We obtain measures of economic mobility and inequality from Chetty et al., (2014). These measures are based on federal income tax records from 1996 to 2012 for more than 40 million individuals who were US citizens in 2013 and had a valid social security number. The dataset includes information from both income tax returns and third-party information returns, providing comprehensive cover of the entire US population.

Third, we obtain rates on entrepreneurship from the Internal Revenue Service's (IRS) Statement of Income (SOI) individual income tax return (Form 1040) statistics. Specifically, we calculate the

[8] Specifically, we have data on the city and state where each participant lives. We match the city to a zip-code using Census Bureau crosswalks and then aggregate the zip-codes to the county level. A small number of zip-codes correspond to multiple counties. For these cases we assign the participant to the county in which the zip-code has the largest share of population.
[9] Indeed, some individuals included in the settlement may have been satisfied customers as noted in at least one article from the popular press (Wieczner, 2016). We believe that our estimates are still valid, although it would imply that we are measuring also where MLM customers are present.
[10] Connectivity is also available between US counties and other countries.

fraction of tax returns containing a Schedule C declaring net income or losses from operating a business or practicing a profession as a sole proprietor relative to the total filed per county. We similarly calculate the S-corporation rate and the household stock market participation rate based on the number of returns claiming ordinary dividends. Sole proprietor, and stock market participation data are the average county value between 2009 and 2015. We use data for the S-corporation for 2013-2015, as the data is unavailable for other years.

Finally, we collect local data on the financial sector and social capital. We collect data on the prevalence of financial institutions, including payday lending, real estate lending, and total establishments from U.S. Census Bureau's County Business Patterns (CBP), an annual data series that provides economic data by industry. We follow the North American Industry Classification System (NAICS) classifications of these establishments as described in Schmid and Walter (2009). In addition, we collect data on social capital using financial complaints from the Consumer Financial Protection Bureau (CFPB). The CFBP provide a database (the Consumer Complaint Data) at the zip-code level on complaints about fraudulent activity. The data from the CFPB is from 2011-2018 and contains the zip code of the complaint filer. We exclude years after 2015 as our measure of MLM incidence is from 2009 to 2015, and exclude approximately 8% (40,000) complaints with incomplete zip codes. We map this data to the county-level by combining the number of Consumer complaints and Consumer fraud complaints and collapsing them to the county-level.

3.2 Summary statistics

We begin by plotting MLM incidence and the average value of the FTC's reimbursement check in Figure 1. Recall that we normalize the per county MLM incidence by population, so that a MLM incidence of 1 corresponds to 1 claim per 10,000 inhabitants. There is considerable dispersion across the United States in both MLM incidence (Panel A) and average payout (Panel B). We observe some concentration for MLM incidence in the southern parts of the United States and in California.

Table 1 provides summary statistics at the county-level. We divide all counties into four groups based on the MLM incidence per inhabitant, and report a T-test in Column 5 of differences in means between the group with the lowest incidence (Column 1) and the group with the highest incidence (Column 4). Variable descriptions can be found in the table notes. Counties with the highest incidence had 83 times as many claims as the counties with the lowest incidence (4.91 compared to 408.96 claims). This is partly a consequence of differing population levels in those counties. When we normalize by county population, Column 1 reports that the counties with the lowest incidence had 1 claims per 10,000 inhabitants, compared to 18.23 claims per 10,000 inhabitants, corresponding to 18 times as many claims per capita. The average payout was also the highest in counties with a higher incidence, $534 compared to $407, although the average claims in Column 2 and 3 are similar in magnitude ($504 and $509, respectively).

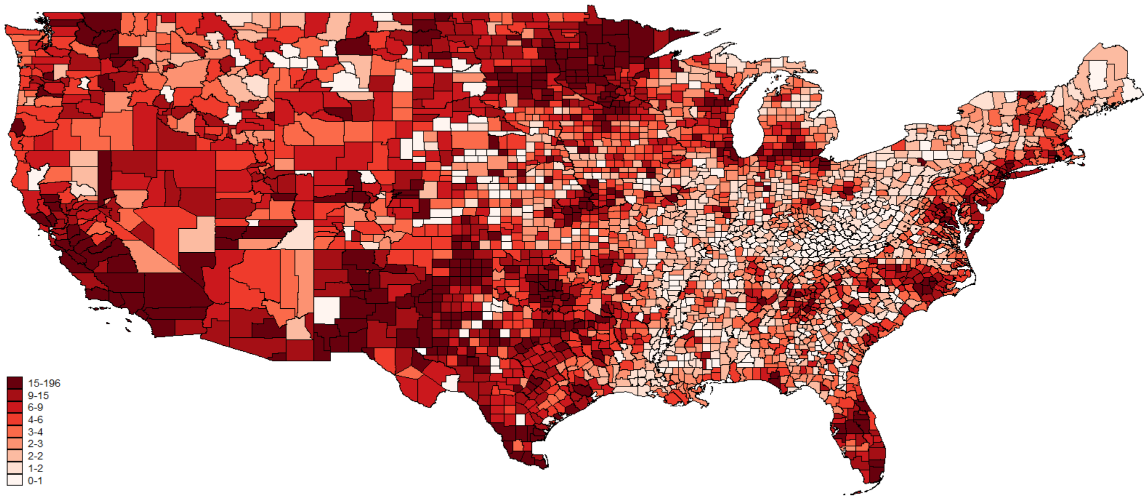
Comparing results for connectivity, we observe that both inside connectivity (defined as own county to own county connectivity) and outside connectivity (defined as the average own-county to outside counties connectivity) is higher for counties with higher incidence. For demographic characteristics, we observe that areas with larger populations, a lower share of State-natives, a lower share of African Americans, a more educated population as measured by the share with a bachelor's degree or more, and a younger population are associated with larger incidence of MLM participation.

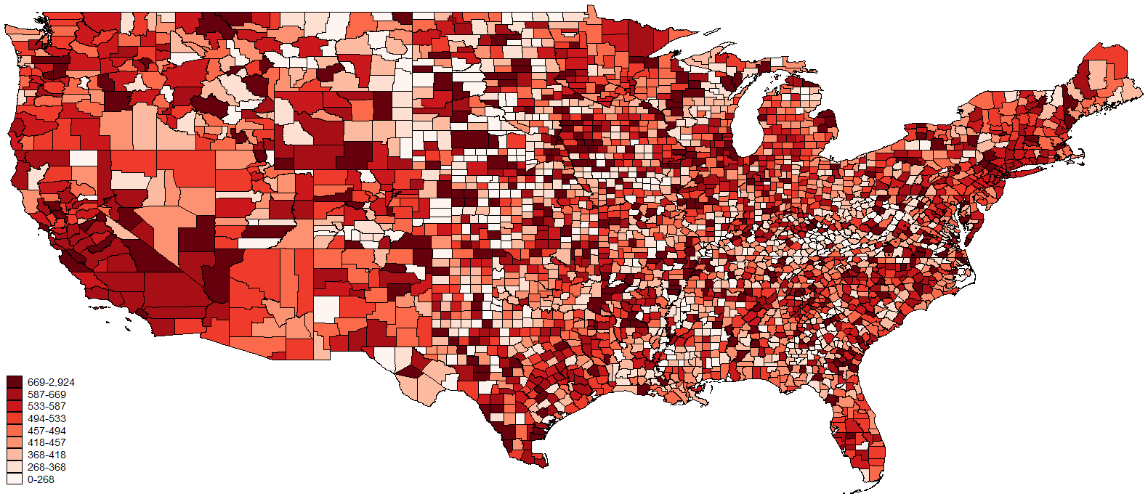
Overall, these results are consistent with the statistics reported in the Direct Selling Association (2017a). Especially important, we find that the share of Hispanic inhabitants is highly predictive of MLM incidence, which corresponds to the facts reported in Direct Selling Association (2017a), and Direct Selling Association (2017b). Finally, median household income and the self-employment share are higher in areas with higher exposure to MLM. This suggests that MLM membership is not necessarily a low-income phenomenon. We will explore income and income mobility in detail further below.

We provide results in graph form in Figure 2. Overall, these results are similar to the results reported in the summary statistics table. All figure use binned scatter-plots to plot MLM incidence (y-axis) against important demographic variables (x-axis). We note that first, MLM incidence is increasing in population size and household median income. There appears to be some clustering in the middle for median income in Panel B, where MLM incidence appears to be higher in the middle of the income distribution. Moreover, median age is negatively correlated with MLM incidence, whereas education level is positively correlated. In Panel E we plot MLM incidence against the Hispanic share of the population.

The result strongly suggests that MLM incidence is increasing in Hispanic share. This result does not appear for other ethnic groups, as we can also see in Table 1. Hispanic communities therefore seem to be particularly involved in MLM activities. Finally, we note in Panel F that the incidence of MLM is correlated with an increasing Gini coefficient, suggesting that participation is concentrated in geographic regions with higher income inequality.

Figure 1. MLM incidence and average payout across the United States





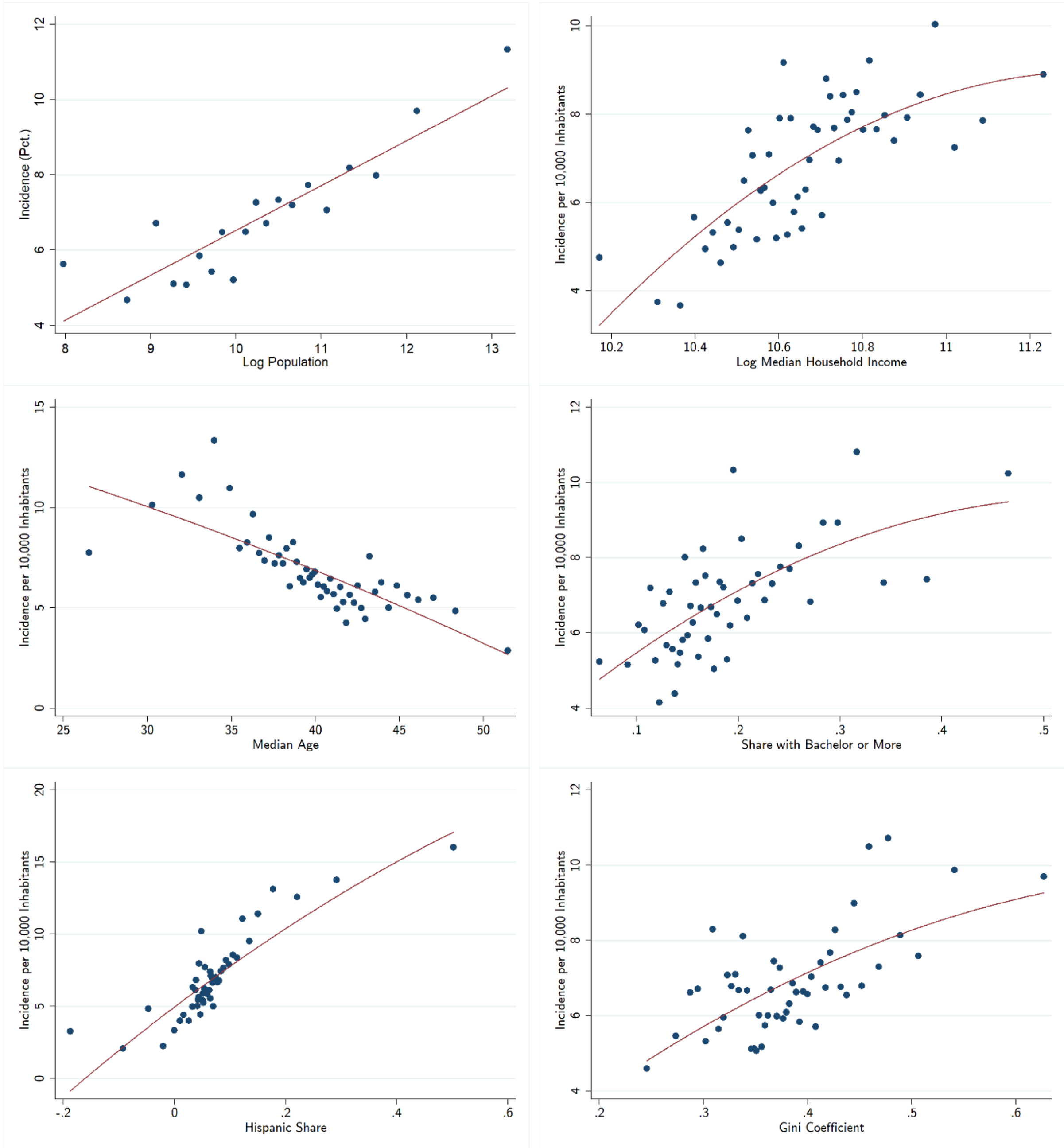
Note: These maps show MLM incidence (Panel A) and the Average FTC refund (Panel B). A darker color corresponds to a higher incidence and a higher average payout. MLM Incidence is scaled by 10,000 inhabitants.

Table 1. Summary statistics

	(1) Low Share	(2) 2	(3) 3	(4) High Share	(5) (4) - (1)
Incidence					
FTC count	4.91	19.03	60.26	408.96	353.69***
	(10.94)	(37.21)	(113.80)	(1,350.11)	[7.76]
FTC share	1.00	2.77	5.61	18.23	17.23***
	(0.55)	(0.58)	(1.29)	(12.93)	[37.74]
Average payout	407.91	504.54	509.32	534.25	168.66***
	(268.44)	(190.56)	(136.99)	(122.02)	[14.33]
Connectivity					
SCI Inside	409.16	622.02	903.64	1,913.65	1,322.81***
	(1,203.86)	(1,632.26)	(2,149.19)	(6,362.35)	[6.05]
SCI Outside	15.71	22.94	42.80	122.69	93.81***
	(129.24)	(61.72)	(108.87)	(365.57)	[7.17]
SCI	3.62	5.43	8.21	16.14	11.01***
	(11.58)	(11.63)	(16.38)	(43.18)	[7.28]
Demographics					
Population	44.18	68.76	103.69	223.05	157.10***
	(100.60)	(134.62)	(186.27)	(594.27)	[7.70]
State native share	75.25	69.74	64.35	62.54	-11.47***
	(10.60)	(12.94)	(14.92)	(15.49)	[-16.69]
White share	83.31	84.35	84.30	82.18	-0.44
	(20.60)	(15.96)	(14.07)	(13.19)	[-0.50]
Black share	12.76	10.50	7.94	6.03	-6.45***
	(20.01)	(15.64)	(12.83)	(9.53)	[-8.31]
Hispanic share	1.03	2.70	7.18	17.35	15.26***
	(3.30)	(4.48)	(10.92)	(18.90)	[21.64]
Median age	40.11	40.17	39.49	37.73	-2.11***
	(3.79)	(4.21)	(4.72)	(4.74)	[-8.49]
Share over 25	67.81	67.48	66.93	65.42	-2.24***
	(4.14)	(4.05)	(4.48)	(4.54)	[-9.14]
Share college	14.96	18.78	21.11	21.96	6.50***
	(6.78)	(7.71)	(9.23)	(9.66)	[15.65]
Income					
Median household income	38.28	43.68	47.07	48.84	9.97***
	(8.42)	(10.27)	(11.83)	(12.57)	[18.73]
Tax returns	17.48	26.87	40.11	80.78	55.64***
	(43.39)	(52.71)	(73.00)	(206.76)	[7.78]
Self-employment share	11.56	13.00	14.00	13.90	2.27***
	(4.33)	(4.52)	(4.47)	(4.37)	[6.95]
Gini	0.39	0.38	0.38	0.40	0.01*
	(0.08)	(0.08)	(0.08)	(0.09)	[1.97]
Absolute Upward Mobility	41.89	42.68	44.27	45.00	3.11***
	(5.00)	(5.09)	(5.60)	(5.53)	[10.77]
Top 1 percent	0.09	0.09	0.10	0.11	0.02***
	(0.04)	(0.05)	(0.04)	(0.06)	[6.18]
Observations	658	724	683	676	1549

Note: We report descriptive statistics: mean and standard deviation for the 3098 U.S. counties in our sample. Columns 1-4 separate the sample by quartile of MLM incidence. Column 5 presents a t-test of differences between the highest quartile of incidence (Column 4), and the lowest (Column 1). Corresponding t-statistics are reported in square brackets. The incidence measures calculated from the data we obtain from the FTC. The count is the raw value of refund checks distributed to households. The share value is per 10,000 county inhabitants. The average payout is the dollar value of refund checks per household scaled by 10,000 county inhabitants. The connectivity measures are derived from the Social Connectedness Index (SCI) from Facebook Inc. The inside value measures connectedness within a county, while the outside value measures connectedness to other counties. These values are weighted by the county's population in 2010. The raw measure provides an average SCI for each county. Demographic measures come from the U.S. Census Bureau's American Community Survey (ACS) and provide the total county population, the share of the population born within the same state, the share with a college degree (at least a bachelor's degree), the share over the age of 25, the median age, and the shares of white, black, and Hispanic individuals within a county. Income measures are obtained from the ACS as well as IRS individual tax returns. Median household income at the county-level is in 1,000 USD. Tax returns states the number of tax returns filed per county in 1,000s. The self-employment share is the fraction of the county's tax returns filed with a Schedule C declaring net income (losses) from sole proprietorship. Standard deviations are in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Figure 2. MLM incidence and demographics



Note: This figure shows binned scatterplots for select demographic variables, where the level of observation is the county. The vertical axis are a number of county-level demographic characteristics that are defined in the notes to Table 1. The red line shows the fit of a quadratic regression. We use 20 bins for the estimation and condition on state fixed effects.

4. Results

The following sections presents our main results. We conduct several analyses to determine how MLM Incidence is correlated with demographics, entrepreneurship, financial development, labor market characteristics, social capital, and social connectivity. Specifically, we run cross-sectional regressions where the dependent variable is the county-level MLM incidence. Unless otherwise specified, we include state fixed effects and a number of control variables defined in the table notes and use robust standard errors.

As previously mentioned, the data that we obtain from the FTC is highly limited in identifying information on MLM participants and we therefore aggregate it the county-level. This means that all stated results are for United States counties and not individuals. To the extent that individuals who participated in the MLM business and received a refund check are similar to the average inhabitant in the county, the below results are consistent. However, even if the average participant differs from the average inhabitant of the county we believe that we contribute important new information about the prevalence of MLM activity, providing important information for better understanding the industry.

4.1 Demographics and labor markets

We begin by correlating MLM incidence against various demographic and labor market variables in Table 2. Consistent with the previous bivariate results, Column 1 reports that population size, Hispanic share and Female share are strongly correlated with MLM incidence, again consistent with what Direct Selling Association reports for the industry as a whole. Recall that 22 percent of the individuals involved in direct selling were Hispanic, compared to their 18 percent share of the US population, and that 74 percent of the individuals involved were female. In Column 2 we observe that median age is strongly negatively correlated with MLM incidence. The share of state-natives in a county is strongly negatively correlated with MLM incidence, perhaps because states with higher inflows of individuals have higher connectivity to the outside and thus greater opportunities for selling to a larger social network. We will explore how connectivity correlates to MLM incidence at a later stage. The self-employment share is not statistically significant, showing that MLM incidence is not higher in areas with more entrepreneurship. We will further investigate this aspect of MLM's in Table 4.

Finally, variables related to income and the income distribution are important determinants of MLM incidence. There is a positive correlation between MLM incidence and log household median income, absolute upward mobility[11], and the Gini coefficient. In other words, MLM incidence is higher in areas with higher income and a more unequal income distribution. This is somewhat contrary to our expectations, as the reporting and indeed the lawsuits against MLM companies allege that these firms are taking advantage of vulnerable households (e.g. Taylor, 2011).

However, this may simply mean that MLM activity is a middle-income phenomenon. Together with the results reported later for female labor force participation, this suggests that MLM activity may primarily be a way for middle-income Americans to gain some extra income – indeed what the industry themselves suggest. However, there are several reasons to be cautious about this interpretation. First, the FTC cut-off for sending checks was losses exceeding $1,000, and low-income households may simply not have exceeded that threshold. Second, joining an MLM as an independent contractor requires that the household has access to financial resources, which may require a certain level of income. Low income household may not be able to afford the

[11] Absolute upward mobility is the expected rank of children whose parents are at the 25th percentile of the national income distribution, from Chetty et al. (2014).

initial costs related to starting a MLM business, which may prohibit them from joining. Third, it is not certain that the individuals who joined the MLM are similar to the median individual in the county, even more likely for counties with higher income inequality. Fourth, a higher incidence in high income counties does not imply that the losses that the individual suffered from joining the MLM are trivial. Higher income individuals may have invested more into their MLM business.

Table 2. Demographic characteristics

	(1)	(2)	(3)	(4)
Log population	0.69***		-0.01	-0.18
	(0.18)		(0.40)	(0.53)
White share	0.41		1.35	-2.29
	(2.59)		(2.62)	(3.21)
Black share	-3.04		0.16	-3.38
	(3.11)		(3.03)	(3.57)
Hispanic share	23.78***		23.27***	26.52***
	(2.52)		(2.54)	(2.92)
Female share	23.64***		30.64***	30.38***
	(6.70)		(6.44)	(7.52)
Median age		-0.30***	-0.12***	-0.12**
		(0.05)	(0.04)	(0.05)
Share college		1.90	-0.30	-2.69
		(4.35)	(6.10)	(7.79)
Log median household income		3.77***	3.85***	4.67***
		(0.88)	(0.89)	(0.99)
Self-employment share		-0.80	0.98	-4.87
		(3.65)	(5.51)	(6.99)
State native share			-6.48***	-6.78***
			(1.43)	(1.47)
Gini				8.86**
				(3.85)
Top 1 percent				-3.96
				(4.68)
Absolute upward mobility				0.12**
				(0.06)
State Fixed Effects	Yes	Yes	Yes	Yes
Observations	3098	3098	3098	2741
Adjusted R^2	0.314	0.266	0.327	0.359

Note: This table presents county-level demographic correlates of MLM incidence across the United States. The dependent variable is the MLM incidence rate scaled by 10,000 county inhabitants. Column 1 includes race and gender compositional measures of the county. The female share is the fraction of women in the total county population, other variables are defined as previous. Columns 2 and 3 include additional characteristics of the county. In Column 4, we include measures of income inequality from Chetty et al., (2014), where Gini represents the income Gini coefficient, Top 1 percent is the fraction of income within county accruing to the county's top 1 percent of tax filers, and absolute upward mobility is the expected rank of children whose parents are at the 25th percentile of the national income distribution. All specifications include state-fixed effects. Robust standard errors are in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

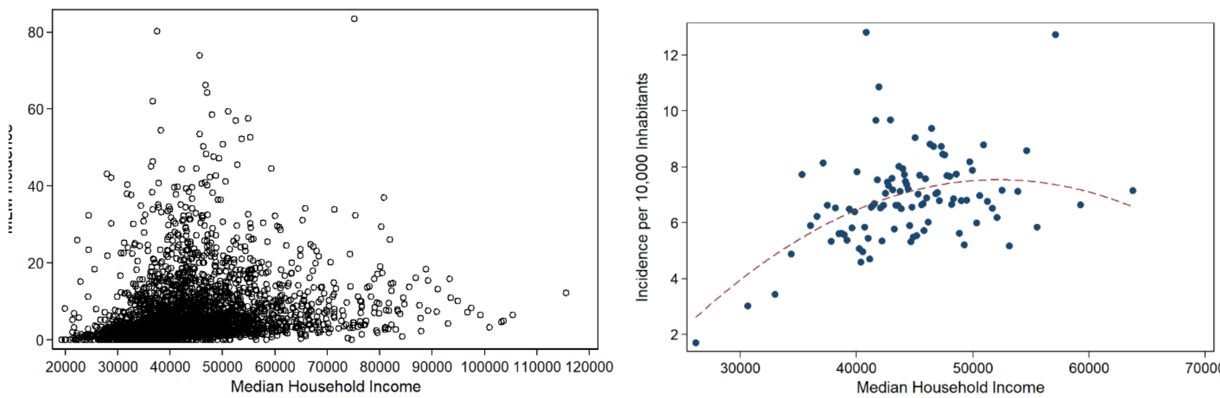
We illustrate the idea about requiring a certain level of income in Figure 3. Specifically, we plot median household income against MLM incident. Panel A uses the raw data in a scatter-plot and panel b uses a binned scatter-plot where we control for the same variables as in Column 4. Overall, our sample shows that MLM was more prominent in middle income counties, where median household income was between $40,000 and $50,000. However, MLM incidence was low in low and high income counties, suggesting that this is a middle-class phenomenon.

As we only have county-level data, we cannot examine whether the individuals actually involved in the MLM have lower or higher income. The Gini-coefficient and absolute upward mobility suggest that MLM's are more common in counties with higher inequality and higher upwards mobility, which may mean that individuals associate themselves with a MLM to achieve a higher status. It is possible that peer effects and relative standing within the community motivate individuals to seek to become entrepreneurs, although this is difficult to test with the data that we have. Our results do not imply that the losses incurred by the individuals in question were marginal to them. We will investigate individual losses in more detail in Table 8 and Table 9. For now, recall that the size of the payout was a partial repayment of the losses that the individual incurred because of their involvement with the MLM in question.

We find that higher income counties also experienced higher losses, as proxied by the size of their check. Figure 4 provides the results. Both panels shows a binned scatter-plot with the log average reimbursement from the FTC on the vertical axis and the log median household income on the horizontal axis. The lower panel includes the same control variables as in Table 2. The results show that the average FTC refund is correlated with higher county-level median income, suggesting that individuals in richer counties put in more resources.

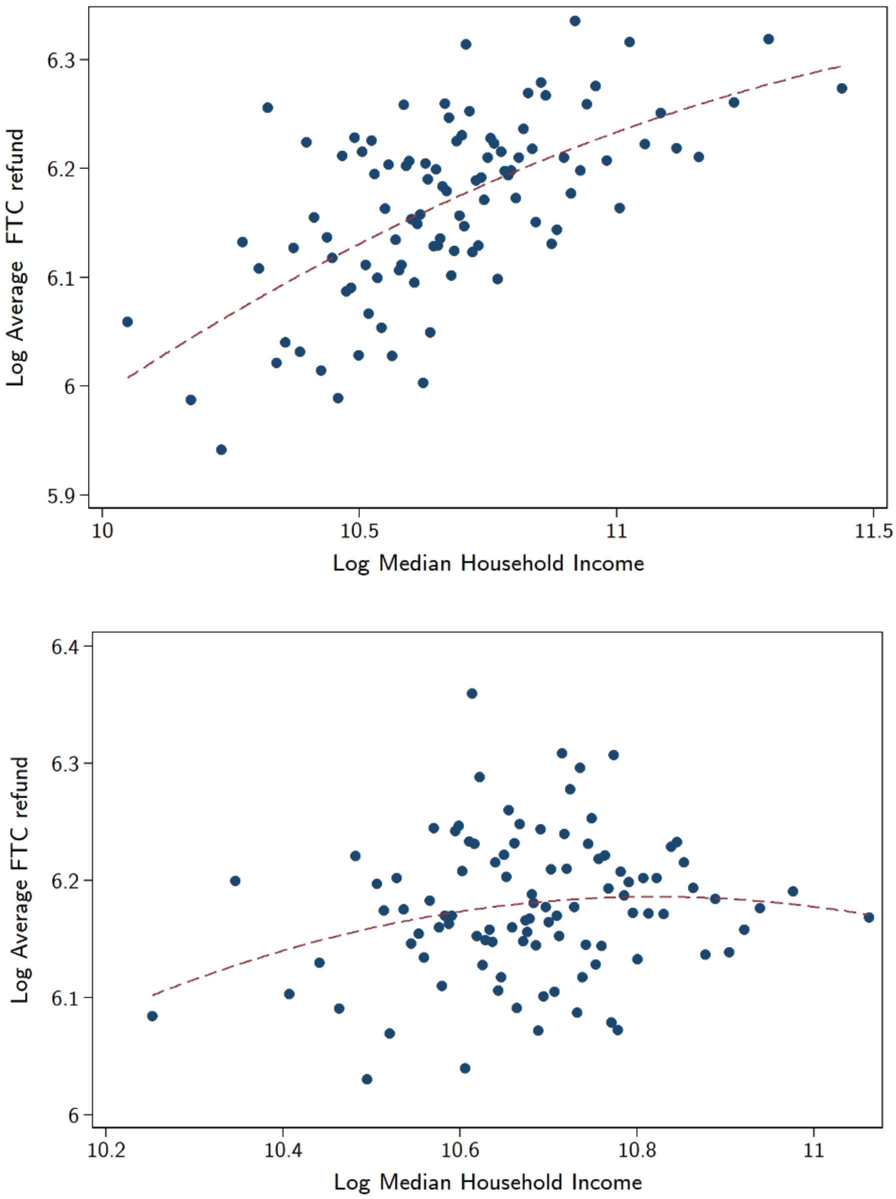
In Table 3, we investigate the role of female labor supply in predicting MLM participation. As descriptive evidence suggests that multi-level marketing is overrepresented by women, we expect that measures of women in the labor force are an important correlate of MLM participation. Columns 1 and 2 show that the number of women in (outside) the labor force relative to the total female population in a county has a positive (negative) effect on MLM participation. However, these variables are not statistically significant. In Column 3, we compute the ratio of women to men that are outside of the labor force within a county. This enters the model positive and statistically significant at the 5% level, indicating that counties with a greater number of non-working women relative to men are linked to a higher MLM incidence within a state.

Figure 3: Household income and MLM incidence



Note: The horizontal axis shows the county-level Median household income and the vertical axis shows the MLM Incidence per 10,000 inhabitants. The first plot shows a scatter plot with all county-level observations except for two outliers with MLM Incidence values over 100. The second plot shows binned scatter-plots for the same variables, where we control for the same variables as in column 4 of Table 2 and include state fixed effects. We use 100 bins in the estimation.

Figure 4: Average payout and household income



Note: The figures shows binned scatterplots without (panel a) and with control variables. The horizontal axis is the Log Median household income and the vertical axis is the Log Average FTC refund in both figures. We use 100 bins in the estimation.

Table 3: Labor force participation

	All counties			Hispanic counties		
	(1)	(2)	(3)	(4)	(5)	(6)
Female labor participation	3.66			13.72*		
	(4.44)			(7.41)		
Female labor nonparticipation		-5.94			-21.15***	
		(3.79)			(6.51)	
Gender ratio of nonparticipation			1.36***			2.06***
			(0.40)			(0.64)
Change in Unemployment	0.21*	0.22**	0.20*	0.38	0.41	0.38
	(0.11)	(0.11)	(0.11)	(0.26)	(0.26)	(0.26)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3098	3098	3098	1550	1550	1550
Adjusted R^2	0.325	0.325	0.328	0.290	0.292	0.293

Note: This table investigates how local area labor force participation correlates with MLM incidence across the United States. The dependent variable is the MLM incidence rate scaled by 10,000 county inhabitants. Female labor participation is the fraction of women in the labor force relative to the total population of the county. Female labor nonparticipation is correspondingly the fraction of women outside of the labor force. The gender ratio is the ratio of labor force nonparticipants of women relative to men. The change in unemployment is the county level change from 2000 to 2009. All specifications control for the following county-level control variables: the log. of 2010 population, the white, black, and Hispanic shares of the population, the female share of the population, the median age of residents within the county, the fraction of individuals with at least a bachelor's degree, the log of median household income, and the fraction of state natives. All specifications include state-fixed effects. Robust standard errors are in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Our interpretation is that this finding supports a "housewife" hypothesis: multi-level marketing participation represents, for some households, a potential business activity that non-working spouses can partake in as an attempt to supplement the household's income. This is likely to be particularly true for MLM's such as Avon, Mary Kay Cosmetics, and other businesses that are traditionally overrepresented among women. This also echoes marketing claims about working from home and on your own schedule, often made by MLM businesses. We note that in counties with above median share of Hispanic households, the coefficients across Column 4 through 6 both increase in magnitude and statistical significance.

Finally, across specifications we control for the change in the county-level unemployment rate between 2000 and 2009, this measure has the additional benefit of capturing the change in unemployment to the bottom of the business cycle. We do find weak evidence that the change in unemployment is positively correlated with MLM incidence, although the effect is not strongly significant.

Katz and Krueger (2017) similarly show that weak labor markets conditions are associated with a rise in alternative work arrangements, such as being an independent contractor. However, they argue that the magnitude of the effect is not large enough to explain the shift from traditional work towards alternative work. We see our results as corroborating evidence that weak labor markets does not substantially explain alternative work arrangements in the form of MLM activity.

We explore the connection between entrepreneurship and MLM incidence in Table 4. If direct selling and independent distribution within an existing MLM business attracts entrepreneurs, we expect to find a positive correlation between regions where there is a high share of sole proprietors and areas containing many previous exposed MLM distributors. We also examine the S-corporation rate, as successful (or experienced) MLM distributors should report business income and associated expenses on Schedule C 1040 tax forms.

Table 4: Entrepreneurship

	All counties			Hispanic counties		
	(1)	(2)	(3)	(4)	(5)	(6)
Sole proprietor rate	-3.02	-6.88	-9.19	-13.18	-24.52**	-33.45**
	(5.88)	(5.85)	(6.98)	(10.68)	(10.54)	(14.74)
S-corp rate		16.83**			43.25***	
		(7.25)			(14.20)	
All establishments per cap			16.83***			37.30***
			(5.78)			(11.26)
Filed tax returns	2.52	2.95	-9.70	1.71	1.94	-32.66*
	(7.50)	(7.56)	(9.07)	(12.04)	(12.09)	(18.07)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3001	3001	3001	1501	1501	1501
Adjusted R^2	0.327	0.328	0.338	0.297	0.302	0.335

Note: This table investigates how self-employment correlates with MLM incidence across the United States. The dependent variable is the MLM incidence rate scaled by 10,000 county inhabitants. Columns 1-3 include all counties in the sample with the exception of 88 where we do not have tax return data. Columns 4-6 restrict the sample to counties above median Hispanic share of the population. The Sole proprietor rate is the fraction of individuals in the county reporting income (losses) from a sole proprietorship, the variable is the 2005-2010 average value. The S-corporation rate is the fraction of individuals filing a tax return for an s-corporation. This variable is the average from years 2013-2015. All establishments provides the number of all business establishments per 10,000 county inhabitants. Finally, filed tax returns is the number of tax returns filed within the county. All specifications include the following county-level control variables: the log. of 2010 population, the white, black, and Hispanic shares of the population, the female share of the population, the median age of residents within the county, the fraction of individuals with at least a bachelor's degree, the log of median household income, and the fraction of state natives. All specifications include state-fixed effects. Robust standard errors are in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

An area with many MLM distributors should be positively correlated with a measure of reported Schedule C tax returns. However, if our measure of MLM incidence measures retailers or individuals unsophisticated or for some other reason unable to file their earnings (losses) and expenses in a Schedule C form, we should find a negative correlation.[12] Similarly, if entrepreneurs form other owner managed businesses, and MLM businesses are a substitute, we should expect to find a negative correlation between high MLM incidence and business activity for counties.

We explore this relationship in Table 4. Columns 1-3 include all counties in the sample, with the exception of 88 where we do not have tax return data. The sole proprietor rate is the fraction of individuals in the county reporting income (or losses) from a sole proprietorship from IRS tax data, and where we use the average value from 2005-2010. The naive estimation in Column 1 indeed shows a positive correlation between sole proprietorship and MLM incidence. As we add control variables in Column 2, however, the relationship between MLM Incidence and the sole proprietor rate becomes negative, but is now not statistically significant. Instead, the S-corp rate becomes positively and significantly correlated with MLM incidence. We find similarly that the number of establishments per capita is positively correlated with MLM incidence, suggesting that areas with a higher MLM share also had more entrepreneurship in general but not as sole proprietors.

Columns 4-6 restrict the sample to counties above median Hispanic share of the population. The coefficient on sole proprietorship is now negative, although not significant in Column 4. In particular, in Column 5 we note that that counties with the highest degree of sole proprietorship have approximately 24 per 10,000 fewer inhabitants exposed to the MLM business, but that counties containing more total establishments and more incorporated business had a higher MLM incidence. Once again,

[12] While there is no minimum income requirement for filing a Schedule C form, business owners are able to file a simplified form if they have expenses less than $5,000, have no employees or inventory, and not using any measures of depreciation or housing deductions.

therefore, the results suggest that counties with a higher MLM incidence had a higher entrepreneurship level in general, just not in the type of businesses that we expect MLM participants to be active in.

Overall, we find MLM incidence is higher in Hispanic communities, in younger and more native counties, in middle income counties, in counties with more unequal income distributions and in areas where unemployment increased more from 2000 to 2009. We find that unemployment levels are not a good predictor of MLM incidence, and that counties with higher entrepreneurial activity but not with more sole proprietors have higher MLM incidence. In general, these results hold when we focus only on Hispanic communities, where MLM activity in general was higher.

4.2 Social connectivity and exposure

We explore the link between MLM incidence and social connectivity in Table 5. Considering that sales in physical locations are often prohibited by MLM companies, social networks such as family and friends are likely to be a main source of potential customers for a participants (Greve and Salaff, 2005; Legara et al., 2008). For example, Greve and Salaff (2005) describes a case study of an immigrant in Canada who uses her social network to recruit new participants and sell products from an American multi-level marketing firm. As our connectivity measures are on the county level, it is important to first discuss our expectations for connectivity. First, it is obvious that the *participant's* connections are what matter, not the county's. Counties do not have social networks, and do not join MLM businesses.

Second, we measure the average county-level connectivity, which essentially calculates how many connections the average person within the county has. A county with more connections may have larger opportunities to profit from a MLM business, as the pool of retail sales and recruitment is larger. However, it is not certain that individual's make this calculation when they are deciding on whether to join an MLM business, or that MLM businesses are more active in areas where social connectivity is high. It is also not obvious that the individuals who join the MLM are the ones with more connections. Individuals who do have large social networks may have more options through their social networks that do not involve a MLM (Montgomery, 1991; Munshi, 2003; Bayer et al., 2008).

Table 5: Social connectivity

	No controls			Controls		
	(1)	(2)	(3)	(4)	(5)	(6)
Log SCI	1.11***			1.32*		
	(0.14)			(0.76)		
Log SCI Inside		0.88***			0.23	
		(0.13)			(0.35)	
Log SCI Outside			0.96***			0.10
			(0.10)			(0.59)
Controls	No	No	No	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3098	3098	3098	3098	3098	3098
Adjusted R^2	0.257	0.254	0.259	0.328	0.327	0.327

Note: This table investigates how connectivity within and across counties correlates with MLM incidence across the United States. The dependent variable is the MLM incidence rate scaled by 10,000 county inhabitants. Log Facebook Connectivity is the log of the average Social Connectedness Index (SCI) for each county. The inside connectivity value measures connectedness within a county, while the outside value measures connectedness to other counties. These values are weighted by the county's population in 2010. All specifications control for the following county-level control variables: the log. of 2010 population, the white, black, and Hispanic shares of the population, the female share of the population, the median age of residents within the county, the fraction of individuals with at least a bachelor's degree, the log of median household income, and the fraction of state natives. All specifications include state-fixed effects. Robust standard errors are in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Even with these caveats in mind, it is still important to investigate the link between MLM incidence and connectivity. First, connectivity to a large extent measures the *potential* profitability for a business that relies on social networks for sales. A high incidence in areas with low connectivity suggest that individuals are not less likely on average to profit from their business, which is important for regulators concerned with MLMs. Second, previous literature has expressed the importance of social ties, networks, and cultural affinity on a variety of financial decisions such as pension savings (Duflo and Saez, 2003), stock market participation and investment behavior (Hong et al., 2004, 2005; Pool et al., 2015), and even participation in Ponzi schemes and fraudulent activity (Gurun et al., 2015; Deason et al., 2015). To understand if MLM participation is spread via close geographical connections rather than more dispersed relationships could provide a valuable insight into predicting areas and socioeconomic groups that may be targeted for involvement into these types of business activities.

In Table 5 we begin by exploring the link between connectivity and MLM participation unconditionally in Column 1-3, followed by the same regressions with the full set of county-level controls in Column 4-6. Column 1 shows that connectivity is highly correlated with MLM incidence. A 1 percent increase in the average social connectivity of a county is associated with an increase in participation of approximately 1.1 individuals per 10,000.

Column 2 and 3 investigates inside versus outside connectivity, e.g., the connectivity within a single county and the connectivity between a county and all other counties in the United States. The regressions suggest that both measures of connectivity are important for MLM participation.

The above result suggest that connectivity is important in explaining MLM activity, but the link becomes once we condition on our set of control variables. In the columns with control variables, inside connectivity is a stronger predictor of MLM incidence than outside connectivity, although statistically insignificant. This result is also shown graphically in Figure 5, Panel A shows a positive relationship between incidence and connectivity. In Panel B, this relationship is less pronounced after including additional county level controls. The findings suggest that MLM activity is higher in areas where the potential to sell through social networks is larger, consistent with more rational behavior on the part of economic agents. However, this could also reflect more marketing towards more attractive areas by MLM companies, or a number of other factors that could determine both connectivity and MLM incidence.

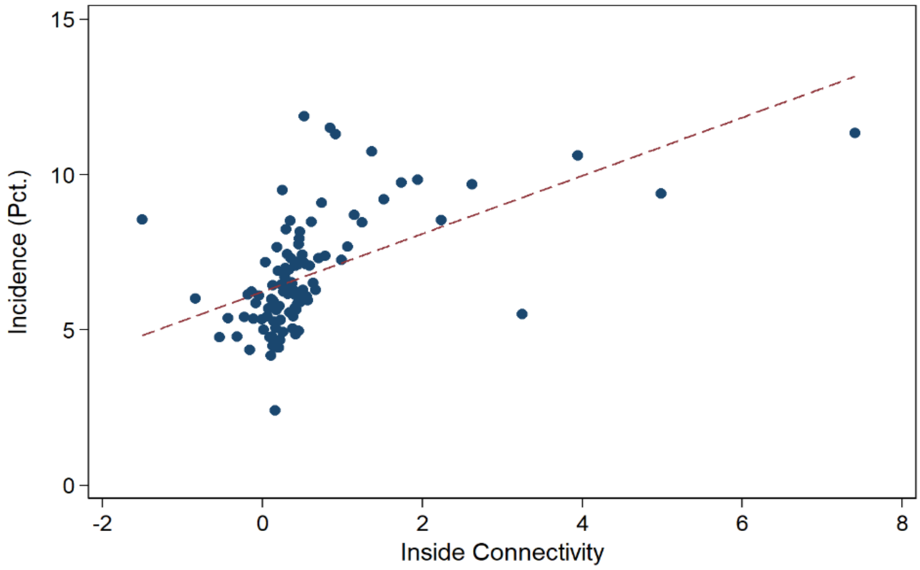
To further examine this point we turn to Table 6, where we explores how connectivity is linked between counties with higher MLM participation. Our hypothesis is that MLM participation is in part spread through person-to-person communication and via social networks. To test this hypothesis we examine the degree to which counties with higher levels of MLM participation are connected via social networks. The variable SCI weighted incidence is the connectivity-weighted county measure of MLM participation while reimbursement is similarly the weighted measure of average payouts from the FTC. Across unconditional and conditional specifications, we find that these two variables enter the model strongly positive and statistically significant. These findings suggest that social connectivity is stronger than average between counties with a high degree of MLM incidence. Our results speak in favor for the hypothesis that social connectivity is linked to MLM participation.

Finally, we investigate how local differences in social capital may influence the incidence of MLM in our sample. As a unique measure of (negative) social capital and trust, we aggregate the number of Consumer complaints and Consumer fraud complaints from the Consumer Complaint Data at the Consumer Financial Protection Bureau (CFPB).[13]

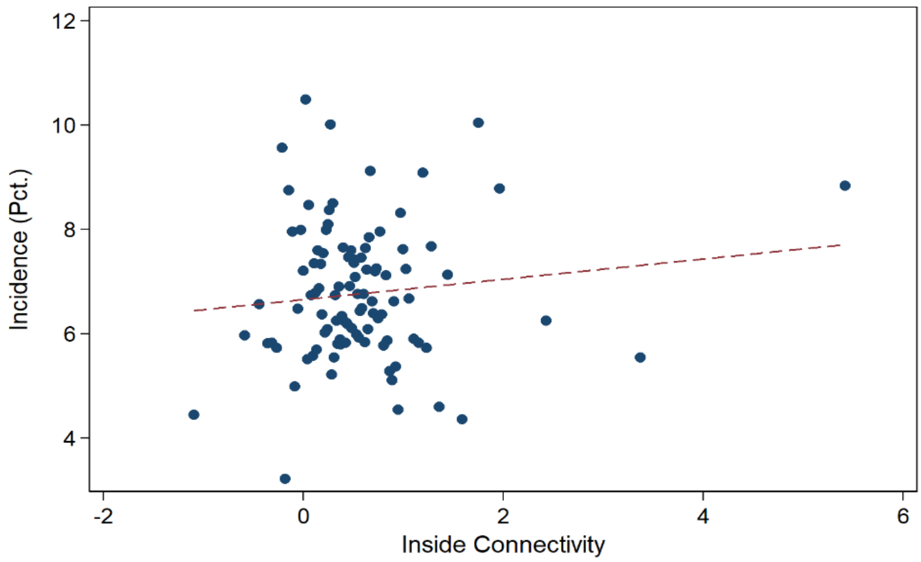
[13] Bricker & Li (2017) use a similar measure of complaints from the Federal Communications Commission (FCC) rather than financially-focused complaints.

Figure 5: Connectivity and MLM incidence

Panel A



Panel B



Note: The horizontal axis shows the county-level log SCI and the vertical axis shows the MLM incidence per 10,000 inhabitants. The first plot does not include controls, and the second plot includes the same variables as in column 4-6 of Table 5 and include state fixed effects. We use 100 bins in the estimation.

Columns 1 and 2 in Table 7 include all counties in the sample, with the exception of 107 counties where we do not match complaint data. All regressions control for the full set of county level characteristics as well as the per capita measure of financial institutions in the county, as recent literature has shown an important relationship between financial development, social capital, and local institutions (e.g. Guiso et al., 2004). In Column 3 we include county level presidential electoral participation rates in the 2008 election, an additional measure of social capital used in recent literature on institutional determinants of financial development (Guiso et al., 2004; Bricker and Li, 2017). Columns 4-6 restrict the sample to counties above median Hispanic share of the population.

Table 6: Social connectivity and MLM incidence

	No controls			Controls		
	(1)	(2)	(3)	(4)	(5)	(6)
Incidence, SCI weighted	1.51***		1.19***		1.19***	
	(0.11)		(0.12)		(0.12)	
Reimbursement, SCI weighted		2.69***		2.10***		2.10***
		(0.17)		(0.21)		(0.21)
Log SCI					1.37*	1.43*
					(0.79)	(0.78)
Controls	No	No	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3098	3098	3098	3098	3098	3098
Adjusted R^2	0.364	0.364	0.394	0.389	0.395	0.390

Note: This table investigates how connectivity within and across counties correlates with MLM incidence across the United States. The dependent variable is the MLM incidence rate scaled by 10,000 county inhabitants. The connectivity weighted incidence measure is the Social Connectedness Index (SCI) weighted average of MLM incidence of other counties connected to county *c*. Similarly the reimbursement variable is the SCI-weighted measure of average per capital refund of each connected county. Log Facebook Connectivity is the log of the average SCI for each county. All specifications control for the following county-level control variables: the log. of 2010 population, the white, black, and Hispanic shares of the population, the female share of the population, the median age of residents within the county, the fraction of individuals with at least a bachelor's degree, the log of median household income, and the fraction of state natives. All specifications include state-fixed effects. Robust standard errors are in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Social capital

	All counties			Hispanic counties		
	(1)	(2)	(3)	(4)	(5)	(6)
Consumer complaints	0.02			0.05		
	(0.01)			(0.07)		
Consumer fraud complaints		0.14			1.30	
		(0.63)			(2.12)	
Electoral participation			-10.20**			-20.71**
			(5.19)			(9.60)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2991	2991	3098	1518	1518	1550
Adjusted R^2	0.334	0.332	0.329	0.298	0.295	0.302

Note: This table investigates how various measures of social capital correlate with MLM incidence across the United States. The dependent variable is the MLM incidence rate scaled by 10,000 county inhabitants. Columns 1 and 2 include all counties in the sample with the exception of 1088 where we do not match complaint data. Columns 4-6 restrict the sample to counties above median Hispanic share of the population. Consumer complaints and Consumer fraud complaints are the aggregate number of complaints and complaints from fraudulent activity county level from the Consumer Complaint Data at the Consumer Financial Protection Bureau (CFPB). Both variables are scaled by 10,000 county inhabitants. Electoral participation is the number of votes cast in the 2008 presidential election scaled by the number of individuals living in the county using 2010 Census estimates. All specifications control for the following county-level control variables: the log. of 2010 population, the white, black, and Hispanic shares of the population, the female share of the population, the median age of residents within the county, the fraction of individuals with at least a bachelor's degree, the log of median household income, and the fraction of state natives. All specifications include state-fixed effects. Robust standard errors are in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Across specifications the coefficients on the social capital measures provide interesting results. Financial complaints and fraud related complaints are positive, albeit not statistically significant across specifications. Furthermore, a greater share of electoral participation is negatively correlated with MLM incidence. The table therefore suggests that MLM participation is more concentrated in areas with lower levels of social capital - as proxied by both consumer complaints and democratic participation rates. As in previous analyses, the effects are accentuated among communities with a higher share of Hispanic individuals.

4.3 Where do MLMs have the greatest negative impact?

As our data and analysis focuses on individuals the FTC cites as having gotten little or no benefit out of their MLM participation, it seems natural to examine attributes of the counties of individuals most negatively impacted by the MLM in terms of financial losses.

In order to examine individual investor losses we exploit the fact that the FTC's lawsuit includes individuals who invested at least $1,000 into the company. As their refund checks are only a fraction of their total realized losses, we scale each individual refund by the minimum check in the sample ($101.94), making the assumption that this value represents the $1,000 minimum investment and larger investments are refunded using a similar calculation. By doing so, we now have a distribution of losses spanning $1,000 to $96,884.24.

We thereby create a dataset with an observations for each individual claimant in the sample, and investigate how county level characteristics correlate with the size of their losses. We cluster standard errors at the county-level, and include state fixed effects as before. Table 8 presents the results.

We note that many county characteristics have qualitatively a similar effect on individual losses as previously shown for MLM incidence. For example, the share of Hispanic individuals is positively correlated while other ethnic groups are negatively correlated with the larger losses. Somewhat surprising, the household median income no longer appears to be a strong positive predictor. Indeed, the coefficient on income changes sign across specifications. Across columns the effect of higher income inequality (the Gini coefficient) is strongly associated with higher investment losses. Our findings for female labor participation, and development of the financial sector also seem to resonate not only with MLM participation as previously discussed, but also with the size of investment losses.

In Table 9, we attempt to account for differences in median income across individuals. Specifically, we repeat the analysis and scale the investment losses variable by the median household income (in $10,000s for legibility). This allows us to examine individual losses relative to the level of income for a representative household within that particularly county. Our findings are qualitatively similar when we scale the investment losses variable. The connectivity measure enters the model positively, suggesting that more connected counties were exposed to higher levels of losses relative to household income. In general, Tables 8 and 9 indicate that investment losses were more severe in counties with a higher share of Hispanics, women, women outside of the labor force relative to men, counties with high income inequality and low educational achievement.

Table 8: Where do MLMs have the largest negative impact?

	(1)	(2)	(3)	(4)	(5)
Log population	0.06*	0.06	0.06*	0.11***	0.41*
	(0.03)	(0.03)	(0.03)	(0.04)	(0.25)
White share	-2.04***	-2.04***	-2.04***	-2.21***	-2.02***
	(0.65)	(0.66)	(0.63)	(0.67)	(0.64)
Black share	-2.75***	-2.67***	-2.36***	-3.10***	-2.60***
	(0.80)	(0.82)	(0.75)	(0.81)	(0.79)
Hispanic share	0.24	0.35	0.18	0.14	0.02
	(0.39)	(0.40)	(0.38)	(0.39)	(0.43)
Female share	-2.67	-2.54	-6.01*	-3.99	-2.22
	(2.88)	(3.01)	(3.37)	(2.91)	(2.88)
Median age	0.01	0.01	0.00	0.02*	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Share college	-1.18**	-1.19**	-0.74	-1.19**	-0.89*
	(0.55)	(0.60)	(0.54)	(0.57)	(0.53)
Log median household income	0.00	0.04	-0.09	0.09	-0.11
	(0.24)	(0.26)	(0.32)	(0.24)	(0.25)
Gini	0.92*	1.16**	0.82*	1.53***	1.13**
	(0.50)	(0.54)	(0.49)	(0.50)	(0.50)
State native share	-1.59***	-1.74***	-1.38***	-1.53***	-1.53***
	(0.43)	(0.45)	(0.41)	(0.42)	(0.41)
Sole proprietor rate		-1.71			
		(1.43)			
Female labor participation			-1.57		
			(1.00)		
Gender ratio of nonparticipation			0.27*		
			(0.14)		
All financial				-0.01	
				(0.01)	
Payday lending				0.08*	
				(0.05)	
All establishments				-0.00***	
				(0.00)	
Log SCI					-0.35
					(0.24)
State Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	334622	313640	334622	334622	334622
Adjusted R^2	0.010	0.010	0.010	0.010	0.010

Note: This table investigates how county level characteristics correlate with individual refund checks scaled into their respective loss amounts. The dependent variable is the refund check scaled by the minimum investment level required for eligibility. The sample consists of all individual refunds in the sample. The independent variables are defined as previous. All specifications include state-fixed effects. Robust standard errors are in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 9: Refund amount – scaled by county median income

	(1)	(2)	(3)	(4)	(5)
Log population	-0.05***	-0.06***	-0.03***	-0.04***	-0.23***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.06)
White share	-0.64***	-0.64***	-0.62***	-0.58***	-0.63***
	(0.19)	(0.19)	(0.17)	(0.20)	(0.18)
Black share	-0.56**	-0.51**	-0.65***	-0.53**	-0.63***
	(0.22)	(0.22)	(0.19)	(0.22)	(0.22)
Hispanic share	0.31**	0.33***	0.20*	0.27**	0.41***
	(0.13)	(0.11)	(0.12)	(0.13)	(0.12)
Female share	3.92***	3.98***	4.45***	3.03***	3.51***
	(0.77)	(0.77)	(0.73)	(0.78)	(0.76)
Median age	-0.01**	-0.01**	-0.02***	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Share college	-1.73***	-1.73***	-1.11***	-1.45***	-1.79***
	(0.12)	(0.12)	(0.12)	(0.13)	(0.12)
Gini	1.07***	1.21***	0.66***	1.22***	0.91***
	(0.11)	(0.11)	(0.11)	(0.14)	(0.13)
State native share	-0.30**	-0.35***	-0.43***	-0.26**	-0.33***
	(0.12)	(0.12)	(0.11)	(0.11)	(0.12)
Sole proprietor rate		-0.48			
		(0.42)			
Female labor participation			-2.18***		
			(0.23)		
Gender ratio of nonparticipation			-0.20***		
			(0.03)		
All financial				-0.01***	
				(0.00)	
Payday lending				0.08***	
				(0.01)	
All establishments				-0.00***	
				(0.00)	
Log SCI					0.17***
					(0.06)
State Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	334622	313640	334622	334622	334622
Adjusted R^2	0.033	0.032	0.036	0.034	0.033

Note: This table investigates how county level characteristics correlate with individual refund checks scaled into their respective loss amounts. The dependent variable is the refund check scaled by the minimum investment level required for eligibility, then scaled by the median household income within that county. The sample consists of all individual refunds in the sample. The independent variables are defined as previous. All specifications include state-fixed effects. Robust standard errors are in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

5. Conclusions

In conclusion, our results suggest that MLM incidence was higher in middle-income and more unequal areas, in areas with relative female labor force participation and in Hispanic areas. Once we condition on covariates the importance of social network is limited, although strong conclusions on connectivity are difficult to given the nature of the data. We do not find strong evidence that MLM activity substitute for unemployment, but we do find some evidence that MLM activity is correlated with certain kinds of entrepreneurship. Finally, we find a positive relationship between financial development and MLM incidence.

Our results highlight the need for further research into the nature of changing labor market and financial vulnerability. For example, it would be crucial to have more detailed data on the individuals who experienced losses for better understanding where MLM incidence had the most damaging impact. Furthermore, detailed data would allow us to study the importance of social networks for both spreading and preventing information could be more closely studied. On one hand, marketing and social connectivity geared toward specific groups (i.e., women, Hispanic, and middle-income households) used as a tool to spread business opportunities seem to resonate strongly with those who incurred losses. On the other hand, these type of targeting criteria to instead sell a positive story could be used to promote financial security, literacy, and investments in relatively safe opportunities.

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