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The Geography of Alternative Work

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Non-Technical Summary

Labor markets are changing. A recent trend is the rise of alternative work arrangements, most able demonstrated by the rise of Uber and similar companies who supply a product but do not formally employ the individuals who sell those products. The share of employees in alternative work arrangements rose by more than 5 percentage points over the past decade, from 10.7 percent to 15.8 percent of the labor force in the United States, a share that is likely to increase as technology advances. Whether this trend is positive or negative for workers is debated, where proponents argue that workers are now able to flexibly set their own schedules and thereby increase their labor supply, and detractors argue that independent work makes for more volatile income and allows companies to avoid paying benefits to workers.

The key in evaluating the relative importance of these two arguments is to understand who participates in alternative work arrangements, since this enables us to determine how many workers are gaining from flexibility and how many are losing from increased insecurity. In this paper we describe the participants in a specific form of intermediated work – *direct selling* through a Multi-Level Marketing (MLM) firm. In a MLM business, individuals join as independent contractors and sell goods provided by the company to their own customers. The business model relies on individual retailers' commission-based product sales direct to customers and on their ability to recruit new members into the company. More than 5 million Americans had a part or full-time involvement as a business builder in a direct-selling company in 2016, corresponding to approximately 3 percent of the labor force, and the total number of Americans involved with direct selling companies increased 30 percent from 2011 to 2016.

We use data from a Freedom of Information Act to the Federal Trade Commission to investigate the geography and determinants of participation with a specific MLM firm. Our data consists of 350,000 individuals who lost money running a MLM business between 2009 and 2015 and whom the FTC reimbursed for a fraction of their losses. We link the participants to a county and examine how county-level determinants correlate with MLM participation, allowing us to evaluate if this type of business attracts individuals who likely value flexibility or if it attracts individuals who would value income security but are unable to achieve it. Because most individuals who join a MLM do not experience any financial gains (in contrast to the often rosy marketing claims), we also evaluate if higher losses are concentrated in areas where individuals can afford them.

Our results suggest that MLM incidence is higher in middle-income and in areas with relative female labor force participation. We do not find strong evidence that MLM activity is a substitute for unemployment, but we do find some evidence that MLM activity is correlated with certain types of entrepreneurship. We also find a positive relationship between financial development and MLM incidence. We find a larger negative impact of MLM activity in counties with a higher Hispanic share, in counties with lower education levels, and in counties with higher income inequality, suggesting that vulnerable individuals are more likely to participate in this type of activity. Most of our results are corroborated with a nationally-representative survey data on direct selling with intermediaries. Overall, our results indicate that the pattern of MLM participation reflects a high value of flexibility, but also that the losses are concentrated in areas that can ill afford to make them. This suggests that the demographic groups most drawn to flexible working arrangements may be also the most vulnerable. Our results highlight the need for further research into the distributional aspects of changing labor market and financial vulnerability.

The Geography of Alternative Work

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Abstract

The increase in alternative working arrangements has sparked a debate over the positive impact of increased flexibility against the negative impact of decreased financial security. We study the prevalence and determinants of intermediated work in order to document the relative importance of the arguments for and against this recent labor market trend. We link data on individual participation and losses from a Federal Trade Commission settlement with a Multi-Level Marketing firm with detailed county-level information. Participation is greater in middle-income areas and in areas where female labor market non-participation is higher, suggesting that flexibility offers real benefits. However, losses from MLM participation are higher in areas with lower education levels and higher income inequality, suggesting that the downsides of alternative work are particularly high in certain demographics. Our results illustrate that the advantages and disadvantages of alternative work arrangements accrue to different groups.

Keywords: Intermediated work; Multi-level marketing; Gig-economy; Entrepreneurship; Consumer financial protection

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1 Introduction

Labor markets are changing. Katz & Krueger (2016) report that the share of employees in alternative work arrangements rose by more than 5 percentage points over the past decade, from 10.7 percent to 15.8 percent of the labor force. This transformation of the labor market is primarily driven by an increase in independent contractors, where individuals work on their own terms and sell directly to customers without being formally employed by the parent company.[1] Whether this trend towards a more entrepreneurial model of the labor market is positive or negative for workers has been debated recently, where proponents of these new types of work arrangements often argue that the increase in flexibility is valuable because it allows workers to arrange their own schedules, and thereby increases labor supply (e.g. Chen *et al.*, 2017; Mas & Pallais, 2017). Meanwhile, the detractors argue that independent work makes for more volatile income and enables companies to avoid paying benefits to workers.[2]

While much of the discussion regarding the advantages and disadvantages of new work arrangements has focused on online intermediaries such as Uber or TaskRabbit, the arguments regarding flexibility and security for workers apply equally to the offline economy. Indeed, two thirds of this type of work is conducted through offline intermediaries (Katz & Krueger, 2016), and the number of Americans affiliated with intermediating firms rose 30 percent from 2011 to 2016 (Direct Selling Association, 2017a). More importantly, however, is how the relative merits of flexibility and security for workers are evaluated. If the majority of workers in intermediated work already have income security and benefits (perhaps through spouses), the argument for improving benefits is less important. Alternatively, if intermediated work is conducted by workers without outside options who lack income security, the argument for benefits becomes more important. Understanding who joins such companies is therefore key in the ability to evaluate the relative weight of the arguments for and against intermediated work.

In this paper we provide an initial examination of the type of individual who participates in a specific form of offline intermediated work - *direct selling*. An individual who is affiliated with a direct selling firm purchases product directly from the firm, but operates independently in their sales and marketing operations. More than 5 million Americans had a part or full-time involvement as a business builder in a direct-selling company in 2016, corresponding to approx-

[1] Oyer (2016) estimate that up to 30% of American workers are involved in independent work.

[2] See Oyer (2016) for an overview of the arguments associated with intermediated work.

imately 3 percent of the labor force, and a further 15 million were directly affiliated (Direct Selling Association, 2017a).[3] We use data from a Freedom of Information Act to the Federal Trade Commission to investigate a particular form of direct selling activity, association with a Multi-Level Marketing (MLM) firm. Individuals join these firms as independent contractors and sell goods provided by the MLM company to their own customers. The business model relies on individual retailers' commission-based product sales direct to customers and on their ability to recruit new members into the company.[4] This type of activity includes an additional concern: most individuals who join a MLM do not experience any financial gains, in contrast to the often rosy marketing claims (Taylor, 2011; Federal Trade Commission, 2016a). We use the FTC data to investigate where MLM activity is most prominent, combining county-level incidences of MLM participation with data on social network connectivity, entrepreneurship, financial characteristics, demographics, social capital, and access to financial institutions, providing new insights into the participants of an increasingly important phenomenon in today's labor markets. Additionally, we corroborate our findings with a nationally-representative survey on participation in direct selling through intermediaries.

Our main findings are that MLM incidence is particularly concentrated in middle-income counties, in counties with higher absolute upward mobility (where individuals are better off compared to their parents (Chetty *et al.*, 2014)), and in counties with higher income inequality.[5] We also find higher incidences of MLM activity in counties with a higher Hispanic share of the population, in areas where female labor force non-participation relative to male non-participation is higher, and in areas with a higher concentration of financial institutions. We do not find that MLM incidence is higher in areas with higher unemployment or higher changes in unemployment, suggesting that MLM participation does not substitute for unemployment. Counties with a high incidence are also more likely to be connected to other counties with high MLM incidence, suggesting that participation in these kind of firms can spread through social

[3]Katz & 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.

[4]The reliance on friends and family to support the business is often crucial, as the parent company often limits many of the standard avenues for retail sales and marketing. For instance, retail sales in physical locations are often prohibited or severely restricted.

[5]It is 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. However, even if we underestimate the incidence of MLM participation we still find that MLM incidence is high in middle-income areas, suggesting that not only low income households participate in this type of activity.

networks. In addition, we find a larger negative impact of MLM activity in counties with a higher Hispanic share, in counties with lower education levels, and in counties with higher income inequality, suggesting that vulnerable individuals are more likely to participate, and more likely to be unsuccessful in this type of activity. Overall, our result indicate that the pattern of MLM participation reflects a high value of flexibility, but also that the losses are concentrated in areas that can ill afford to make them. This suggests that the costs and benefits of alternative work arrangements may accrue to different demographics – middle income areas enjoy the benefits, while unequal and lowly educated areas pay the cost.

To date, we are not aware of any existing empirical or theoretical literature about the type of individuals who join a MLM company. This is perhaps not surprising, as data about who participates and their characteristics are difficult to obtain. Many of the firms involved are privately held, or 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 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 measure the strength of social connections within and between counties across the United States using the Social Connectedness Index from Facebook. Since traditional forms of advertising and attracting customers are often prohibited by the MLM company itself, a participant in a MLM often relies on social networks of friends or family for the recruitment of new customers and new participants. The Direct Selling Association states that more than 70% of sales of all MLM businesses are through a direct person-to-person channel, with an additional 20% percent 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, 2015). Our results show that the overall connectivity of a county is an important correlate of MLM participation, primarily driven by connectivity within the same county. We also find that counties with MLM incidence are connected to other counties with high MLM incidence. However, once we condition on control variables we find a much weaker relationship between MLM activity and social connectivity.

MLM activity does not appear to strongly substitute for unemployment (Katz & Krueger, 2017). Unemployment levels are not a good predictor of MLM incidence, even though there is (weak) evidence that MLM incidence is higher in counties that experienced larger unemployment shocks during the Great Recession. Further, counties with higher entrepreneurial activity in general have higher MLM incidence, but not counties with more sole proprietors. Our analysis using survey data show that individuals and households who have prior experiences (direct or through other members of the household) with self-employment are drawn to direct selling and the use of intermediaries.

Reassuringly, we find that the demographics of our FTC data correspond to micro data from the RAND-Princeton Contingent Work Survey, as well as 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. 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.

While we find a positive correlation between MLM incidence and county-income levels, this does not imply that the losses experienced by an individual through an MLM are trivial or that higher benefits or more employment security would not be valued by the workers. In fact, we find that counties with higher income also experienced larger losses from participating in a MLM business opportunity, as proxied by the size of the FTC's settlement checks. We investigate where individual's lost the most by examining the size of their refunds, both in absolute terms and relative to county median income. 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.

By focusing specifically on MLM businesses we shed light upon an important vulnerability in today's society, improving our understanding of who invest in projects that regulators continue to warn consumers against.[6] 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 the extent that we are able to measure it, these results suggest that that our results generalize to other firms acting as intermediaries in the industry. At the same time, evidence from survey data highlights important differences between individuals who participate in direct selling with and without an intermediary. 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.

Our research expands upon recent literature on the changing nature of employment in the United States (Katz & 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 & 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. Relatedly, Burtch *et al.* (2018) analyze how online intermediaries influence local entrepreneurial activity by showing that entrepreneurship (measured with survey data and Kickstarter campaigns) decreases in local areas after the introduction of Uber.

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. 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 Gurun *et al.* (2015), who suggest that trust and shocks to trustworthiness are spread through closely-

[6]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."

knit social networks, and Deason *et al.* (2015) who reiterate the importance of cultural affinity in propagation of previous fraudulent activities collected from the Securities and Exchange Commission (SEC).

Our study proceeds as follows: In Section 2 we discuss related literature and the institutional basis of our study. Section 3 presents our data sources and the sample. In Section 4, we discuss our findings of determinants of MLM participation across different dimensions. Section 5 concludes.

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 & 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 & Krueger (2016) specifically investigate the role of direct selling to customers by conducting a survey in association with the RAND American Life Panel.[7] 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. In total 20.5 million individuals were involved in direct selling in 2016, up from 15.6 million in 2011.[8] 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). The DSA estimates that direct sales generated $35.84 billion of revenues in 2016 in the United States, mainly through person-

[7] We utilize information from this survey in Section 4.6.

[8] 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.

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 participants are paid commissions, bonuses, discounts, dividends, and/or other forms of payment in return for selling products or recruiting members (Albaum & 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. Indeed, participants are often prohibited from selling the products in a physical store, leaving direct sales within social networks as the only viable option for generating revenues (Greve & 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. With fixed sales prices, lowering the cost for products and operations becomes increasingly important for generating profits. 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).

The importance of direct sales is sometimes limited, and 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 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 dependent on profits, but are instead based on revenues or earnings, potentially from the (initial) purchases of new recruits (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. In contrast, Albaum & 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. Moreover, 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).[9]

The over-reliance on recruitment for producing revenues and exaggerated claims about potential profitability for the average participant has received criticism (Koehn, 2001) and 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. Furthermore, the FTC 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 FTC cite the company's own numbers stating that sales to customers outside the company network accounts for 39 percent of product sales (Federal Trade Commission, 2016a, p.18). The lawsuit was eventually settled in 2016, with the company agreeing to pay $200 million and restructure their business. The FTC used the payment to partially refund nearly 350,000 distributors who lost money, using company records to identify participants who incurred losses (Federal Trade Commission, 2016b).

[9] Income and earnings from employment opportunities in the the broader alternative and independent work space have also been noted to be volatile and '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 described above, 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 the checks 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 county population. We also drop military, international, and non-continental US addresses.[10] Our unit of observation will therefore be the county, as we do not have more information about the individuals other than were they live and the size of their check.[11]

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) report that the index is based on more than 220 million active US users in 2016, with representative coverage of the full population. We use this data to better understand the social nature of MLM

[10] 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. We scale this value by 10,000 individuals for legibility.

[11] Some individuals included in the settlement may have been satisfied customers as noted in at least one article from the popular press (Wieczner, 2016).

participation. The index provides a measure of connectivity within a county, but also for each county-pair in the United States.

Second, we collect data on income mobility, demographics, unemployment, income and income inequality. We use data 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 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.

We collect local data on the financial sector and social capital. Data on the prevalence of financial institutions, including payday lending, real estate lending, and total establishments originates 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 & 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.

Finally, we leverage a recent wave of the RAND-Princeton Contingent Work Survey, a version of the Contingent Worker Survey from the RAND American Life Panel. The survey wave was conducted by Katz & Krueger (2016) in October and November 2015.[12] This survey allows us to measure individual-level determinants of participation in direct selling businesses, including individuals who work with direct selling intermediaries, much like our FOIA dataset. The survey covers approximately 3,800 individuals and was originally designed to be nationally-representative. The RAND corporation provides weights adjusted to the Current Population Survey providing comparable results to our county-level sources of data from the Census Bureau and the Bureau of Labor Statistics.

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. Since MLM incidence is highly concentrated in Hispanic communities (Direct Selling Association, 2017b), where relevant we consider results for counties with an above median Hispanic share.

As the data we obtain from the FTC is highly limited in identifying information on MLM participants, we aggregate the data at 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

[12] Please refer to Katz & Krueger (2016) for full details regarding this survey and the questionnaire.

industry and the trend towards more alternative work arrangements.

4.1 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 particularly observe 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). When we normalize by county population, Column 1 reports that the counties with the the lowest incidence had 1 claims per 10,000 inhabitants, compared to 18.23 claims per 10,000 inhabitants. 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. 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 bachelors degree or more, and a younger population are associated with larger incidence of MLM participation. 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 scatterplots 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, and MLM incidence is 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. Finally, Panel F shows that the incidence of MLM is correlated with an increasing Gini coefficient, showing that participation is concentrated in geographic regions with higher income inequality.

4.2 Demographics and labor markets

In the section we investigate the correlation between MLM incidence and various demographic and labor market variables. The results are presented 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. Reassuringly, this is consistent with what the Direct Selling Association reports for the industry as a whole, providing supporting evidence that our results on the geography of alternative work generalize to the direct selling 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 further explore how connectivity correlates to MLM incidence at a later stage.

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,[13] and the Gini coefficient. In other words, MLM

[13] 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).

incidence is higher in areas with higher income, in areas where individuals are better off compared to their parents, and a more unequal income distribution. This is somewhat contrary to our expectations, as the media and indeed the lawsuits against MLM companies allege that these firms are taking advantage of vulnerable households (e.g. Taylor, 2011). 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.

There are several reasons to be cautious about these results. First, the FTC cutoff 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 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. Finally, a higher incidence in high income counties does not imply that the losses individuals suffered from joining the MLM are trivial. Higher income individuals may not have invested more into their MLM business. We will return to this last point in section 4.5.

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 scatterplot and Panel B uses a binned scatterplot where we control for the same variables as in Column 4. Overall, our sample shows that MLM incidence was more prominent in middle income counties, where median household income was between \$40,000 and \$50,000. MLM incidence was low in low and high income counties, suggesting that participation is a middle-class phenomenon. As our main source of data is at the county-level, we cannot examine whether the individuals actually involved in the MLM have lower or higher income. Survey evidence in Section 4.6 suggests that middle-income households may be more likely to participate in MLMs. At the county-level, the Gini-coefficient and absolute upward mobility suggest that MLM participation is 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.

In Table 3, we investigate the role of 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 inside (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. Our interpretation of this finding supports a "housewife" hypothesis: multi-level marketing participation represents, at least for certain 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 MLMs 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. Finally 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.

In Table 4 we continue our investigation of labor markets by examining how unemployment rates correlate with MLM incidence. In particular, we are interested in exploring whether MLMs to some extent are a substitute for other job opportunities for unemployed workers (Katz & Krueger, 2017) and whether a larger increase in unemployment during the financial crisis induced more MLM activity in the county. For an individual looking for an opportunity for self-employment or for a job, an MLM may offer an easier solution than an entirely new firm, as it is possible to leverage the existing infrastructure provided by the company. For instance, the individual joining an MLM can order products directly from the company which removes the need to create a new supply chain, and likely has access to marketing material and other best-practice sales pitches, which may help an unexperienced entrepreneur in getting started.

We correlate unemployment levels in 2000 and 2009 with MLM incidence in Column 1 and

2. In Column 3 we examine the change in unemployment between 2000 and 2009. We use the rate of unemployment in 2000 to measure unemployment prior to the housing boom, and use 2009 because our affected sample was active in the MLM from 2009 to 2015. Changes between 2000 and 2009 has the additional benefit of capturing the change in unemployment until the bottom of the business cycle.

We do not find any evidence that the county-level unemployment rate correlates with MLM incidence in Column 1 and 2. We do find weak evidence that the change in unemployment is positively correlated with MLM incidence in in Column 3, although the effect is not strongly significant. Moreover, given the strong correlation between MLM activity and the Hispanic share, we examine whether changes in unemployment mattered more for Hispanic communities. Specifically, we create a dummy variable equal to one for all counties with an above median Hispanic share and a dummy variable equal to one for all counties with an above median change in unemployment. We interact these variables with each other in Column 4. Combined, the result suggest that MLM incidence was slightly higher in areas with both high unemployment and a high Hispanic share.

Katz & 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 do not substantially explain MLM incidence, although unemployment seems to matter more in Hispanic communities.

We explore the connection between entrepreneurship and MLM incidence in Table 5. 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. Successful (or experienced) MLM distributors should report business income and associated expenses on Schedule C 1040 tax forms. We also examine the S-corporation rate, as overall entrepreneurship rather than self-employment may be correlated with preferences for MLM-style businesses.

In Table 5, we explore the relationship between entrepreneurship and MLM incidence. 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 2009-2015. 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. The number of establishments per capita is positively correlated with MLM incidence, suggesting that areas with a higher MLM share also have more entrepreneurship activity 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, 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. We will explore this connection in greater detail in Section 4.6 using survey data.

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 in general 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.

4.3 Financial inclusion and social capital

In this section we continue by exploring the relationship between MLM participation and the financial sector and various measures of social capital. Three main issue motivate our approach. First, financial sector development often plays a crucial for entrepreneurship by providing financing to new and existing ventures. If participating in a MLM business requires financial resources, the financial sector may help provide capital and loans to fund the participant. Second, the financial sector plays an important role in monitoring entrepreneurs and new firms. This is potentially of additional importance for MLM firms, where the FTC and other organizations warn about the legitimacy of these businesses. By providing information to the potential participants in an MLM industry, the financial sector could potentially steer individuals away from less legitimate firms. Third and finally, on the individual side, we are interested in the role of household financial development and literacy on MLM participation.

Several studies have shown the importance of basic financial concepts for explaining stock market investments (Van Rooij *et al.*, 2011), retirement savings (Lusardi & Mitchell, 2007), and that financial literacy varies across demographic groups (Lusardi *et al.*, 2010; Lusardi & Mitchell, 2008). Given the warnings that the FTC has provided about MLMs, we find it relevant to examine MLM activity through the lens of financial literacy. Since we do not have access to measures on financial literacy on the county-level, we use proxies that intend to capture different levels of financial literacy. In particular, we consider *payday lending* an important proxy for household financial development and literacy, as payday lending is correlated with harmful effects such as bankruptcy (Skiba & Tobacman, 2015), difficulties paying bills (Morse, 2011), and financial stress and disruptions in job performance (Carrell & Zinman, 2014). A higher share of these firms in a county may indicate that the population there is having troubles with their finances.

Table 6 investigates the degree to which access to various types of financial institutions is correlated with MLM participation. Moving across columns of the table, we note that counties with a higher degree of MLM incidence are correlated with a higher per capita measure of banking establishments. This is driven not by savings banks, but rather by real estate related financial services and payday lending store locations, although payday lending is only weakly correlated.

Previous research has found that access to payday lending can help consumers smooth liquidity positions over expenditure shocks (Morse, 2011). For example, Bhutta (2014) finds that access to payday lending has no effect on individual credit scores, delinquencies, or overdrawing credit lines. However, given that other institutions would be providing the same services for a lower price, a higher prevalence of payday lending at the very least proxies for financial constraints and arguably also for financial literacy.

Next, 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).[14]

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 as an additional measure of social capital used in recent literature on institutional determinants of financial development (Guiso *et al.*, 2004; Bricker & Li, 2017). Columns 4-6 restrict the sample to counties above median Hispanic share of the population.

Across all specifications the coefficients on financial complaints and fraud related complaints are positive but not statistically significant. A greater share of electoral participation is negatively correlated with MLM incidence. The results are therefore inconclusive regarding social capital and MLM incidence, except for electoral participation.

4.4 Connectivity and exposure

We explore the link between MLM incidence and social connectivity in Table 8. 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 & Salaff, 2005; Legara *et al.*, 2008). For example, Greve & 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

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

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 individual's who join the MLM are the ones with more connections. Individuals who do have large social networks may have more employment options through their social networks that do not involve a MLM (Montgomery, 1991; Munshi, 2003; Bayer *et al.*, 2008).

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 & 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 8 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 naive regressions suggest that both measures of connectivity are important for MLM participation.

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 may be spread via social networks. If these types of opportunities spread and are exacerbated via social networks and social connectedness, it presents an actionable insight to mitigate the risk for vulnerable households in the future. Examining this aspect of labor markets is therefore not only relevant for the industry at large, but also for individuals' from the general population when considering the benefits and costs of choosing this type of self-employment.

Overall, the result suggest that connectivity is important in explaining MLM activity, but that the results are weaker once we condition on our set of control variables. Moreover, inside connectivity is a stronger predictor of MLM incidence than outside connectivity, although statistically insignificant. 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 9, 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.

4.5 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 counties that were most negatively impacted by the MLM in terms of financial losses.

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 5 provides the results. Both panels shows a binned scatterplot 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 wealthier counties invest more resources.

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, with an average (median) loss of $5,663 ($3,784). We create a dataset with 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 10 presents the results.

Many county characteristics have a qualitatively 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 11, 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 10 and 11 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, and counties with high income inequality and low educational achievement. Finally, as previously noted, financial development also seems to matter as counties with more payday lending establishments were more severely affected.

4.6 Determinants of direct selling: Evidence from survey data

We complement our county-level results on MLM participation with micro-data on participation in direct selling through an intermediary. Specifically, we rely on a recent wave of the RAND-Princeton Contingent Work Survey, a version of the Contingent Worker Survey from the RAND American Life Panel. This survey, conducted in October and November of 2015, contains rich demographic information about households and their participation in direct selling organizations, and has been used to provide valuable insights into alternative work arrangements in Katz & Krueger (2016). Furthermore, respondents are weighted in line with the Current Population Survey, which means that the results will be qualitative comparable to our county-level results that use data from the Census Bureau and the Bureau of Labor Statistics.

We use this dataset is to explore the correlations we have shown at the county level. Table 12 provides these results. The columns across the table are indicator variables which take the value of one for different types of direct selling involvement. In Column 1, we investigate participation in any direct selling business. The variable takes the value of one if the subject answered yes to the question *'on either your main job or a secondary job, do you do direct selling to customers?'*. In Column 2 (3), the variable indicates that the individual is involved with direct selling in his or her main (secondary) job. Finally, in Column 4 the dependent variable takes the value of one if the individual answered yes to the following question: *'Do you work with an intermediary, such as Avon or Uber, in your direct selling activity?'*.

The results across the table provide important, additional context to our previous analysis. The coefficients are the odds ratios after a logistic regression.[15] A coeficient value greater than one therefore indicates a positive correlation of the explanatory variable in explaining participation in direct selling, whereas a value less than one indicates that the explanatory variable is less likely to predict direct selling. We note in Columns 1 and 2 that participation in direct selling to customers is overrepresented by white men. In addition, individuals involved in direct selling seem to be correlated with self employment and entrepreneurial behavior.[16] While this contradicts our main results, however, note that this column includes all direct-selling activity. When we focus on direct selling as a secondary employment opportunity in Column 3 and direct selling through a direct-selling intermediary, we find correlations that closely correspond to our previous results. First, Hispanic women are heavily overrepresented when direct selling is part-time or through an intermediary. Second, although not statistically significant, we note with the coefficients for income terciles two and three, that middle-income households are more likely to work with a direct selling intermediary. This finding is also supported in Figure 6, where we plot the odds ratios for each household income decile predicting participation in direct selling with an intermediary. We present this result as additional evidence that MLM participation is likely to be a middle-income phenomena. However, note that these results have large confidence intervals, not surprising given the small sample distributed across bins. Finally, we note that entrepreneurial activity, both as main employment and also represented in other household members, strongly predicts uptake into direct selling with an intermediary.

In Table 13 we explore the link between types of direct selling and reported income. Columns 1 and 4 present ordered logit regressions where the dependent variable is the self reported income bracket associated with either all income in Columns 1-3, or income from direct selling intermediaries or alternative working arrangements. For further comparison we include indicators as the dependent variables in Columns 2, 3, 5, and 6, which take the value of one if the

[15] While Katz & Krueger (2016) include only individuals who worked in the previous week from the survey, we include the full sample surveyed in this wave of the CWS.

[16] Katz & Krueger (2016) note that the CWS may overrepresent self-employed workers. To address this, and make their results more nationally-representative they construct an alternative weighting measure. We obtained these weights from the authors and confirmed that our results are qualitatively similar regardless of the weights used. Our results are therefore presented with the original RAND provided weights for ease of use for other researchers.

earnings from all sources or direct selling is less than \$5,000; less than \$500; or less than the median earnings.[17] Presenting the coefficients again in odds ratios, we note that for all sources of income, individuals involved in direct selling are approximately 0.34 times more likely to earn a higher bracket of income. However, this effect is negative for individuals working with direct selling intermediaries. Of particular interest is Column 6, where we find that individuals in direct selling are less likely to earn under median earnings when working in direct selling, however participants of direct selling with intermediaries are more than 2.5 times more likely to be earning under median income.

5 Conclusion

In this paper we provide an initial examination of the type of individual who participates in offline intermediated work with Multi-Level Marketing firms, a substantial and understudied aspect of labor markets. We use MLM participation across the United States to understand where alternative working arrangements are prevalent and which types of households may value the benefits of flexibility relative to the downsides of employment insecurity and risk.

Our results suggest that MLM incidence is higher in middle-income and more unequal areas, in areas with relative female labor force participation and in Hispanic areas. We do not find strong evidence that MLM activity is a substitute for unemployment, but we do find some evidence that MLM activity is correlated with certain types of entrepreneurship. Finally, we find a positive relationship between financial development and MLM incidence. Overall, our result indicate that the pattern of MLM participation reflects a high value of flexibility, but also that the losses are concentrated in areas that can ill afford to make them. This suggests that the demographic groups most drawn to flexible working arrangements may be also the most vulnerable.

Our result highlight the need for further research into the nature of changing labor market and financial vulnerability. For example, more detailed data would allow us to study the importance of social networks for both spreading and preventing information. It is also crucial to have more detailed data on the individuals who experienced losses for better understanding where MLM incidence has had the most damaging impact, and if individuals participate in multiple

[17] \$5,000 and \$500 correspond to the lowest income brackets available to survey respondents for total, and direct selling income.

MLM business opportunities and other direct selling businesses over time.

References

Albaum, Gerald, & Peterson, Robert A. 2011. Multilevel (network) marketing: An objective view. *The Marketing Review*, **11**(4), 347–361.

Bailey, Michael, Cao, Ruiqing Rachel, Kuchler, Theresa, Stroebel, Johannes, & Wong, Arlene. 2017. *Measuring social connectedness.* Tech. rept. National Bureau of Economic Research.

Bayer, Patrick, Ross, Stephen L, & Topa, Giorgio. 2008. Place of work and place of residence: Informal hiring networks and labor market outcomes. *Journal of Political Economy*, **116**(6), 1150–1196.

Bhutta, Neil. 2014. Payday loans and consumer financial health. *Journal of Banking & Finance*, **47**, 230–242.

Bricker, Jesse, & Li, Geng. 2017. Credit Scores, Social Capital, and Stock Market Participation.

Burtch, Gordon, Carnahan, Seth, & Greenwood, Brad N. 2018. Can You Gig It? An Empirical Examination of the Gig Economy and Entrepreneurial Activity. *Management Science.*

Carrell, Scott, & Zinman, Jonathan. 2014. In harm's way? Payday loan access and military personnel performance. *The Review of Financial Studies*, **27**(9), 2805–2840.

Chen, M Keith, Chevalier, Judith A, Rossi, Peter E, & Oehlsen, Emily. 2017. *The value of flexible work: Evidence from uber drivers.* Tech. rept. National Bureau of Economic Research.

Chetty, Raj, Hendren, Nathaniel, Kline, Patrick, & Saez, Emmanuel. 2014. Where is the land of opportunity? The geography of intergenerational mobility in the United States. *The Quarterly Journal of Economics*, **129**(4), 1553–1623.

Cook, Cody, Diamond, Rebecca, Hall, Jonathan, List, John, Oyer, Paul, *et al.* 2018. *The Gender Earnings Gap in the Gig Economy: Evidence from over a Million Rideshare Drivers.* Tech. rept. The Field Experiments Website.

Deason, Stephen, Rajgopal, Shivaram, & Waymire, Gregory. 2015. Who gets swindled in Ponzi schemes?

Direct Selling Association. 2017a. Direct Selling in 2016: An Overview. *https://www.dsa.org/docs/default-source/research/growth-outlook/dsa_2016gandofactsheet.pdf?sfvrsn=6*. Online: Accessed: 2018-02-22.

Direct Selling Association. 2017b. The Value of Direct Selling to Hispanic Americans. *https://www.dsa.org/docs/default-source/direct-selling-facts/the-value-of-direct-selling-to-hispanic-americans_2.pdf?sfvrsn=2*. Online: Accessed: 2018-02-22".

Direct Selling News. 2017. DSN Announces the 2017 Global 100! *https://www.directsellingnews.com/dsn-announces-the-2017-global-100/*. Online: Accessed: 2018-02-22".

Duflo, Esther, & Saez, Emmanuel. 2003. The role of information and social interactions in retirement plan decisions: Evidence from a randomized experiment. *The Quarterly journal of economics*, **118**(3), 815–842.

Dunn, Jancee. 2015. Swell of Tupperware-Type Parties Overwhelms City Dwellers. *New York Times*. https://www.nytimes.com/2015/11/29/fashion/direct-sales-parties-for-city-slickers.html. Online. Accessed on 2018-03-01.

Federal Trade Commission. 2016a. Case No. 2:16-cv-05217: COMPLAINT FOR PERMANENT INJUNCTION AND OTHER EQUITABLE RELIEF. *https://www.ftc.gov/system/files/documents/cases/160715herbalifecmpt.pdf*. Online: Accessed: 2018-03-01.

Federal Trade Commission. 2016b. Case No. LA CV16-05217 STIPULATED ORDER FOR PERMANENT INJUNCTION AND MONETARY JUDGMENT. *https://www.ftc.gov/system/files/documents/cases/160725herbalifeorder.pdf*. Online: Accessed: 2018-03-01.

Greve, Arent, & Salaff, Janet W. 2005. Social network approach to understand the ethnic economy: A theoretical discourse. *GeoJournal*, **64**(1), 7–16.

Guiso, Luigi, Sapienza, Paola, & Zingales, Luigi. 2004. The role of social capital in financial development. *American economic review*, **94**(3), 526–556.

Gurun, Umit G, Stoffman, Noah, & Yonker, Scott E. 2015. Trust busting: The effect of fraud on investor behavior. *The Review of Financial Studies*.

Hong, Harrison, Kubik, Jeffrey D, & Stein, Jeremy C. 2004. Social interaction and stock-market participation. *The journal of finance*, **59**(1), 137–163.

Hong, Harrison, Kubik, Jeffrey D, & Stein, Jeremy C. 2005. Thy neighbor's portfolio: Word-of-mouth effects in the holdings and trades of money managers. *The Journal of Finance*, **60**(6), 2801–2824.

Katz, Lawrence F, & Krueger, Alan B. 2016. *The rise and nature of alternative work arrangements in the United States, 1995-2015*. Tech. rept. National Bureau of Economic Research.

Katz, Lawrence F, & Krueger, Alan B. 2017. The role of unemployment in the rise in alternative work arrangements. *American Economic Review*, **107**(5), 388–92.

Koehn, Daryl. 2001. Ethical issues connected with multi-level marketing schemes. *Journal of business ethics*, **29**(1-2), 153–160.

Legara, Erika Fille, Monterola, Christopher, Juanico, Dranreb Earl, Litong-Palima, Marisciel, & Saloma, Caesar. 2008. Earning potential in multilevel marketing enterprises. *Physica A: Statistical Mechanics and its Applications*, **387**(19-20), 4889–4895.

Leuz, Christian, Meyer, Steffen, Muhn, Maximilian, Soltes, Eugene, & Hackethal, Andreas. 2017. *Who Falls Prey to the Wolf of Wall Street? Investor Participation in Market Manipulation*. Tech. rept. National Bureau of Economic Research.

Lusardi, Annamaria, & Mitchell, Olivia S. 2007. Baby boomer retirement security: The roles of planning, financial literacy, and housing wealth. *Journal of monetary Economics*, **54**(1), 205–224.

Lusardi, Annamaria, & Mitchell, Olivia S. 2008. Planning and financial literacy: How do women fare? *American Economic Review*, **98**(2), 413–17.

Lusardi, Annamaria, Mitchell, Olivia S, & Curto, Vilsa. 2010. Financial literacy among the young. *Journal of consumer affairs*, **44**(2), 358–380.

Mas, Alexandre, & Pallais, Amanda. 2017. Valuing alternative work arrangements. *American Economic Review*, **107**(12), 3722–59.

Montgomery, James D. 1991. Social networks and labor-market outcomes: Toward an economic analysis. *The American economic review*, **81**(5), 1408–1418.

Morse, Adair. 2011. Payday lenders: Heroes or villains? *Journal of Financial Economics*, **102**(1), 28–44.

Munshi, Kaivan. 2003. Networks in the modern economy: Mexican migrants in the US labor market. *The Quarterly Journal of Economics*, **118**(2), 549–599.

Oyer, Paul. 2016. The Independent Workforce in America.

Pool, Veronika K, Stoffman, Noah, & Yonker, Scott E. 2015. The people in your neighborhood: Social interactions and mutual fund portfolios. *The Journal of Finance*, **70**(6), 2679–2732.

Schmid, Markus M, & Walter, Ingo. 2009. Do financial conglomerates create or destroy economic value? *Journal of Financial Intermediation*, **18**(2), 193–216.

Skiba, Paige Marta, & Tobacman, Jeremy. 2015. Do payday loans cause bankruptcy?

Statement. 2016. Statement of Average Gross Compensation. *http://www.herbalife.com/Content/en-US/pdf/business-opportunity/statement-of-average-gross-compensation-usen.pdf6*. Online: Accessed: 2018-02-22.

Taylor, Jon M. 2011. Who Profits from Multi-Level Marketing (MLM)? Preparers of Utah Tax Returns Have the Answer.

Van Rooij, Maarten, Lusardi, Annamaria, & Alessie, Rob. 2011. Financial literacy and stock market participation. *Journal of Financial Economics*, **101**(2), 449–472.

Wieczner, Jen. 2016. Herbalife Paid a $200 Million Fine. Then the FTC Screwed it Up. *Fortune*. http://fortune.com/2016/07/15/herbalife-bill-ackman-settlement-ftc/ Online: Accessed: 2018-03-01.

6 Figures

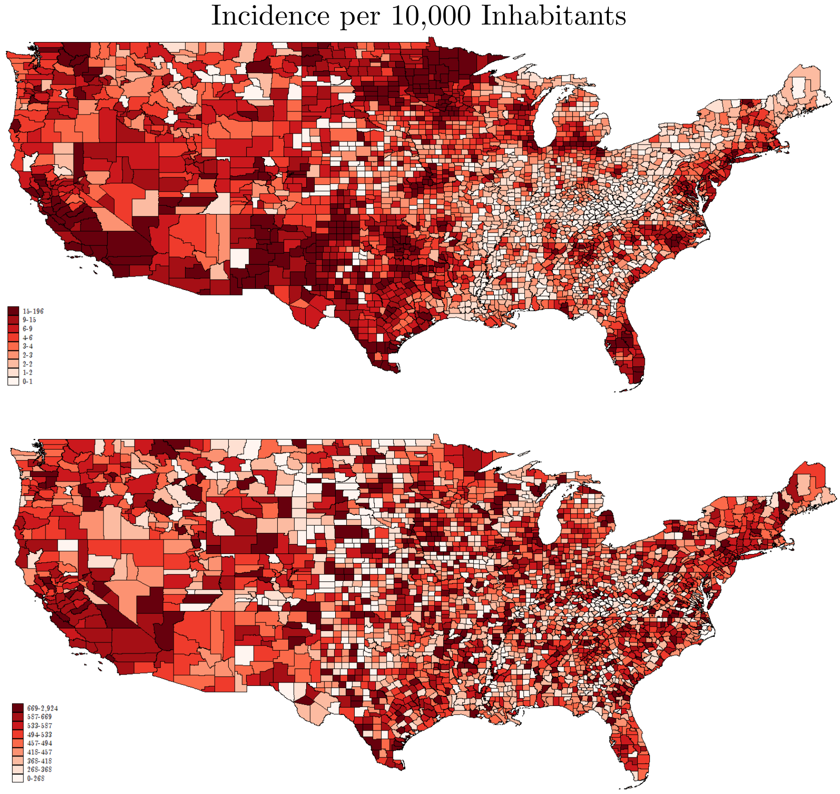


Figure 1: MLM Incidence and Average Payout Across the United States

Note: The 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.

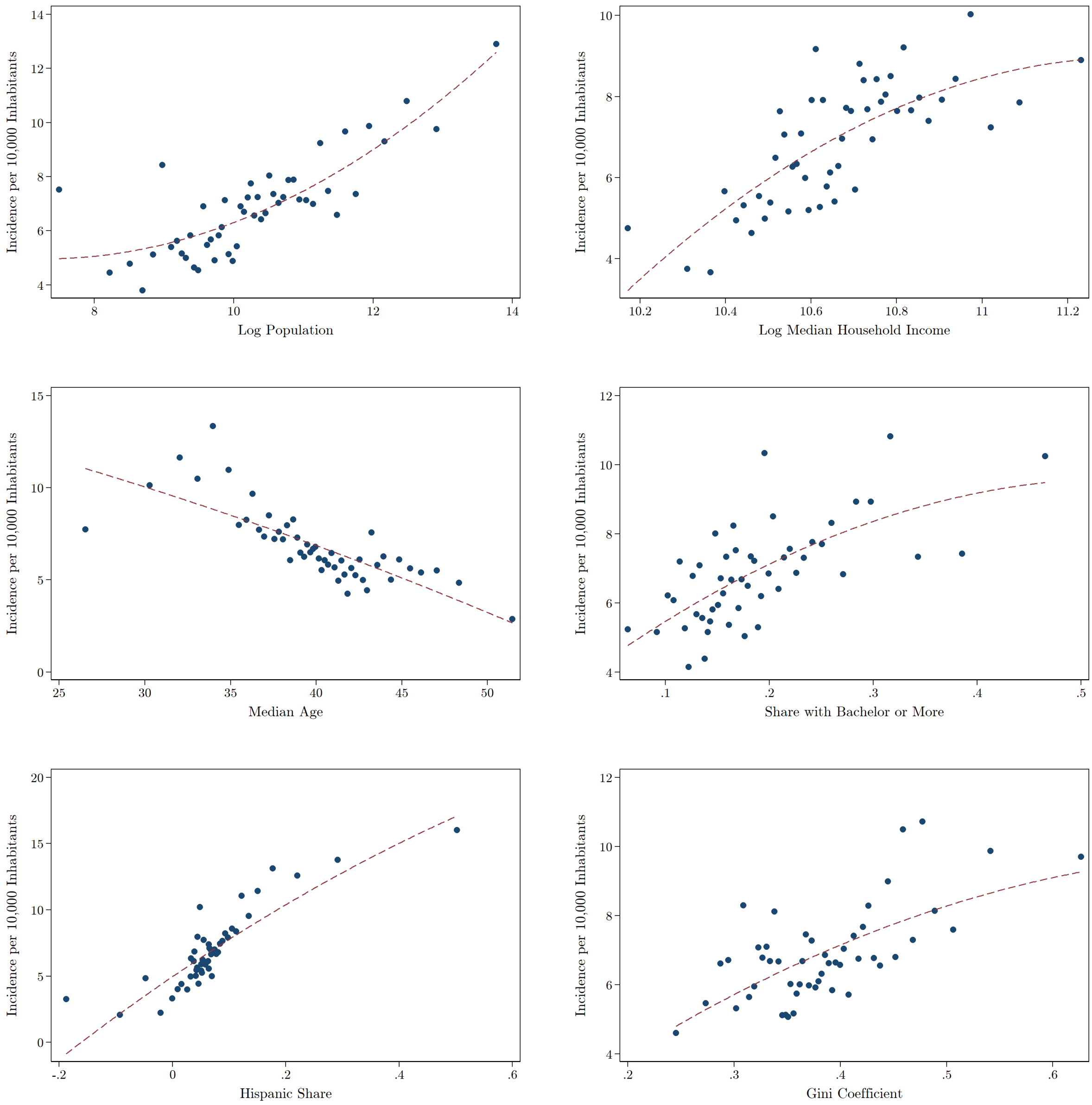


Figure 2: MLM Incidence and Demographics

Note: The 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.

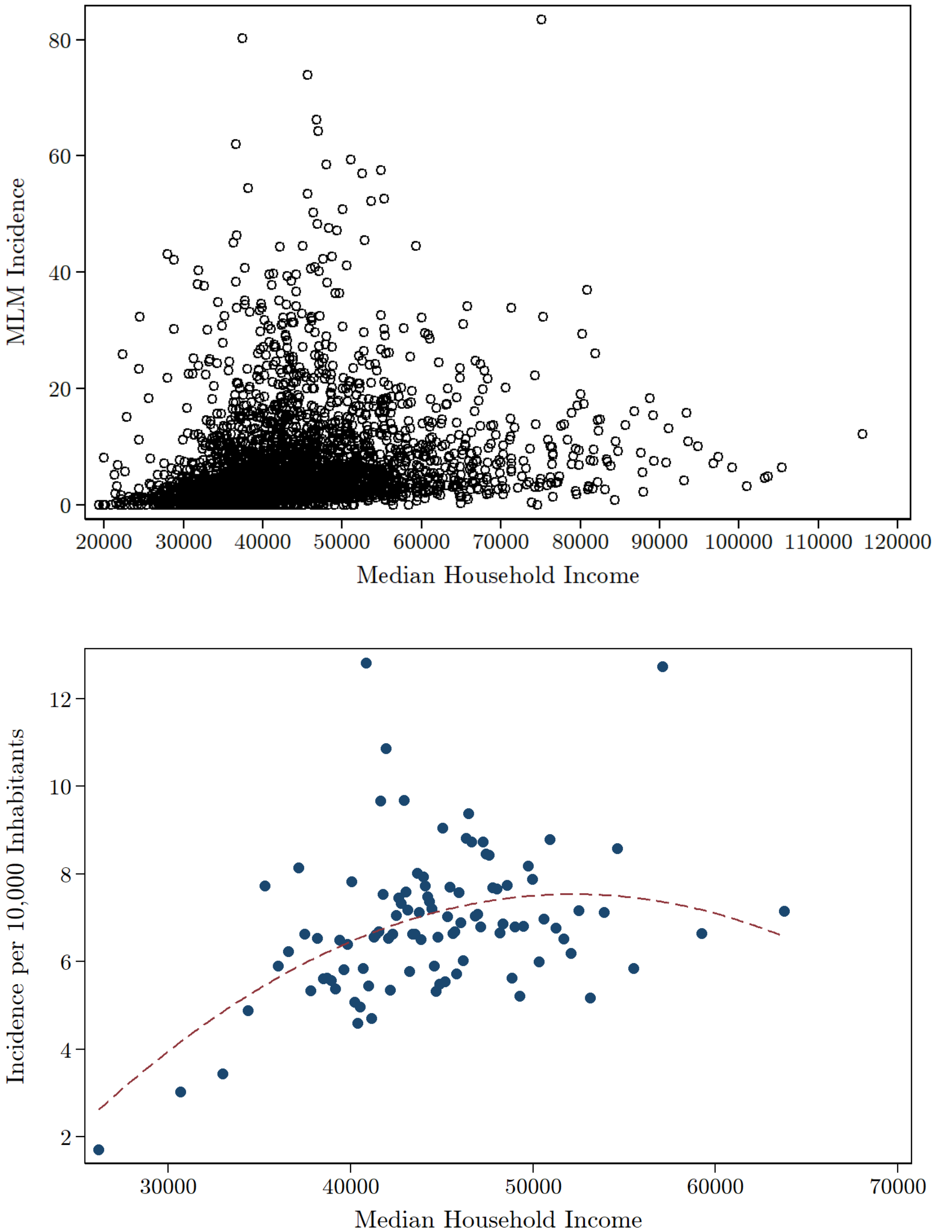


Figure 3: Household Income and MLM Incidence

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 scatterplots 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.

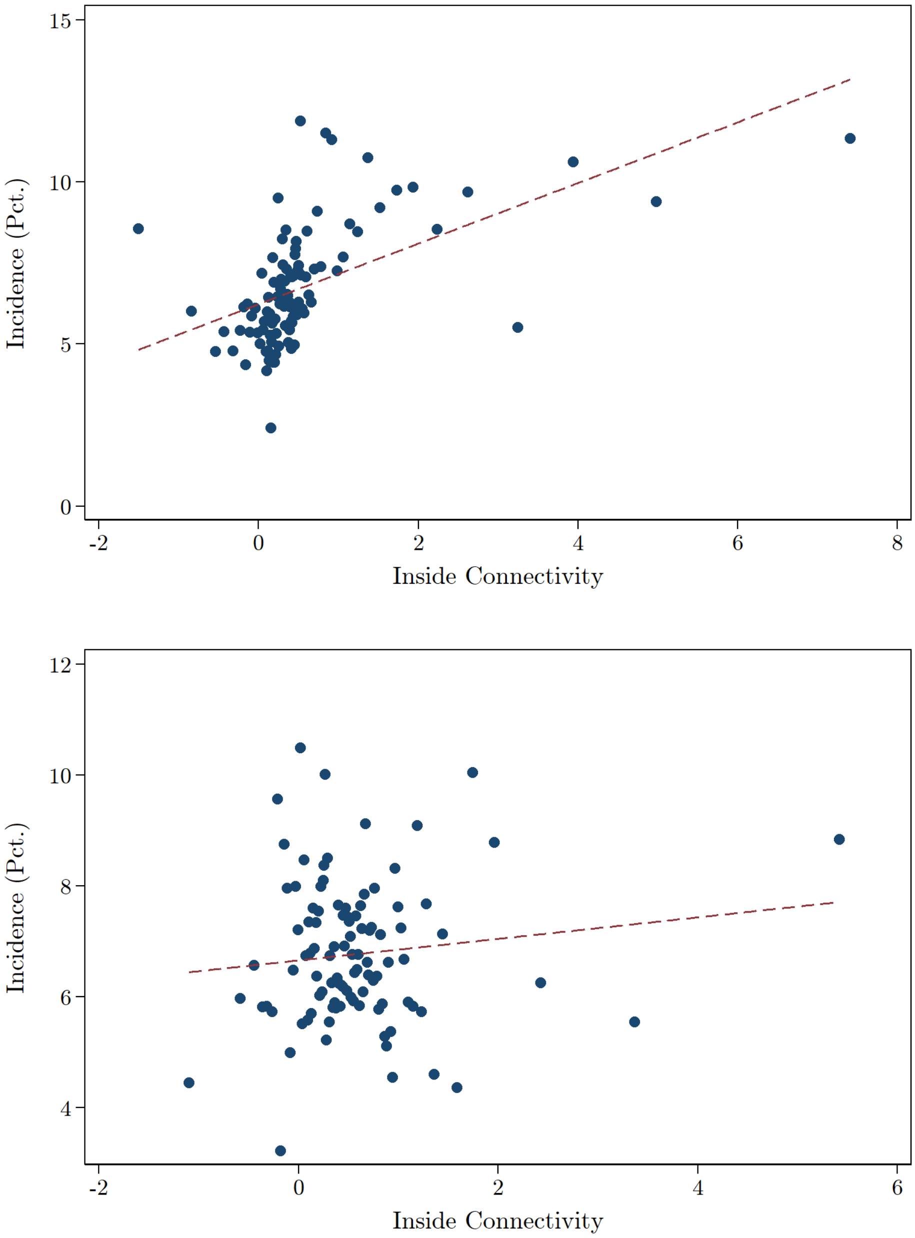
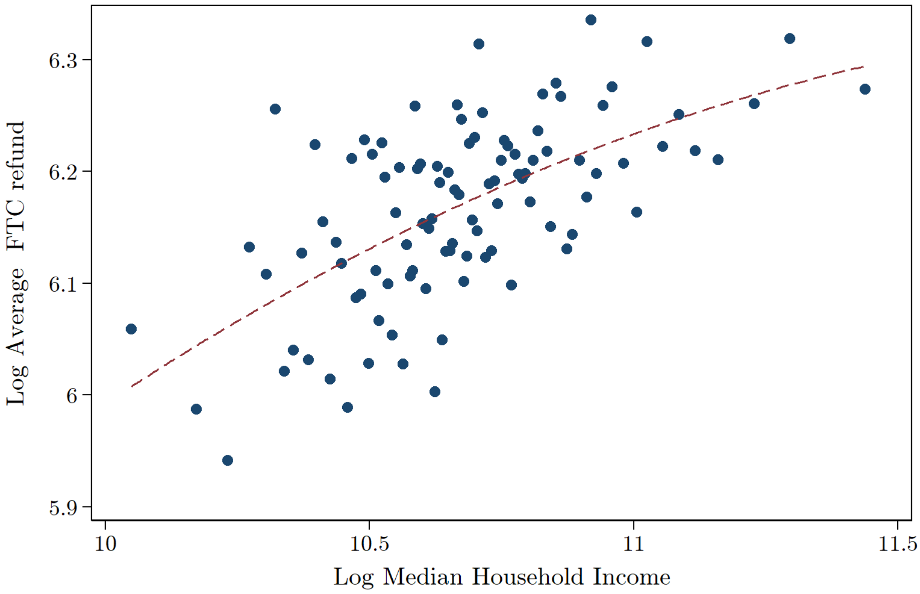


Figure 4: Connectivity and MLM Incidence

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 Columns 4-6 of Table 8 and include state fixed effects. We use 100 bins in the estimation.



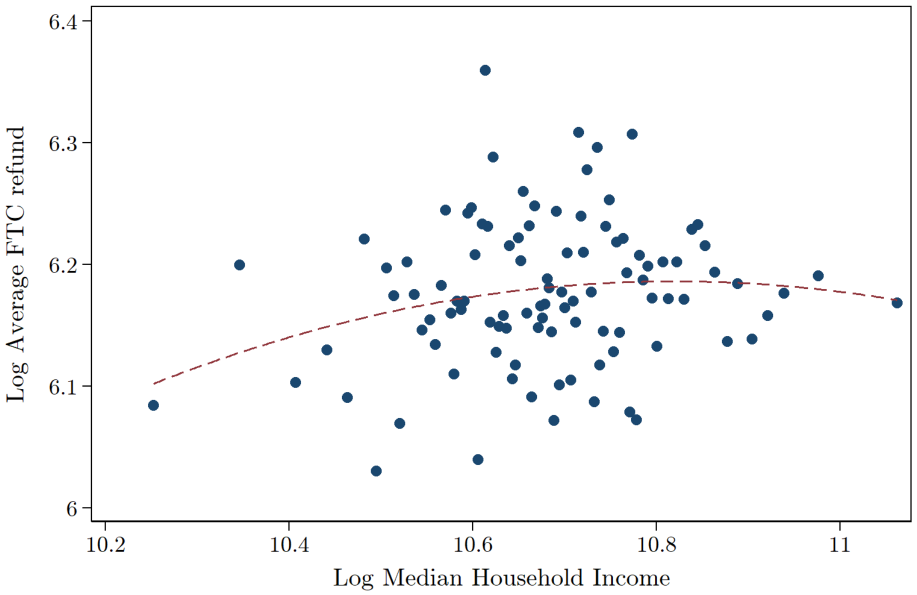


Figure 5: Average Payout and Household Income

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.

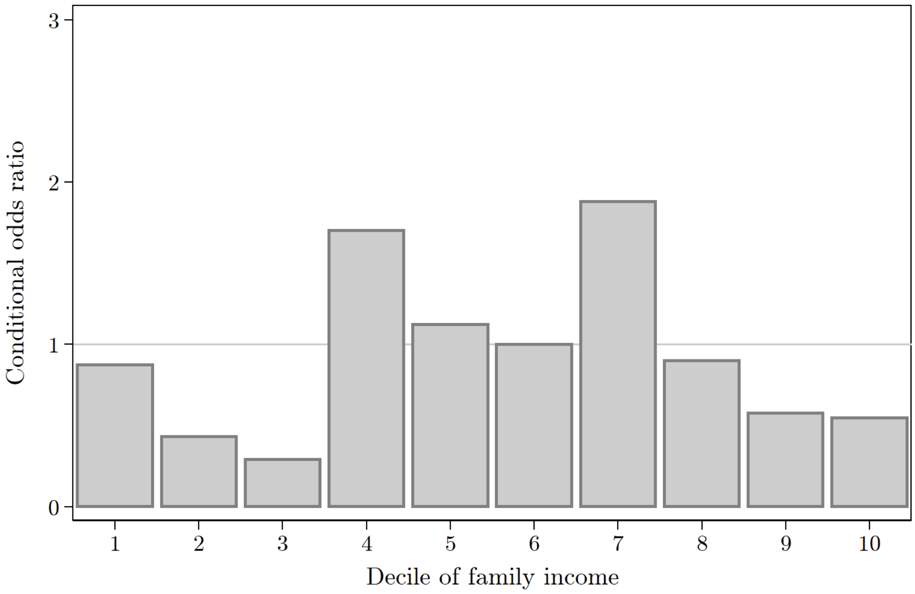


Figure 6: Direct Selling with Intermediaries and Household Income

Note: This figure presents odds ratios after a logistic regression predicting a positive outcome for working with a direct-selling intermediary. We include control variables for Hispanic and white races, gender, age and age-squared, married, and college education. Confidence intervals are large due to the small sample size across bins, and therefore unreported for scale.

7 Tables

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

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 bachelors 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.

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	3,098	3,098	3,098	2,741
Adjusted R^2	0.326	0.279	0.340	0.374

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.

Table 3: Laborforce 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	3,098	3,098	3,098	1,550	1,550	1,550
Adjusted R^2	0.337	0.338	0.340	0.315	0.317	0.319

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.

Table 4: Unemployment

	(1)	(2)	(3)	(4)
Unemployment 2000	-0.15			
	(0.17)			
Unemployment 2009		0.11		
		(0.11)		
Change in Unemployment			0.20*	
			(0.11)	
Above median Hispanic share				-2.03***
				(0.51)
Above median change in unemployment				-0.13
				(0.51)
High unemployment * High Hispanic share				2.46***
				(0.66)
Controls	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes
Observations	3,098	3,098	3,098	3,098
Adjusted R^2	0.340	0.340	0.341	0.345

This table investigates how local area unemployment correlates with MLM incidence across the United States. The dependent variable is the MLM incidence rate scaled by 10,000 county inhabitants. Unemployment is measured by the Census Bureau at the county level in year 2000 and year 2009. The change in unemployment is the change from 2000 to 2009. Above median Hispanic share is an indicator which takes the value of one for counties with an above median share, similarly above median change in employment takes a value of one for counties with high increases in unemployment. The final variable in the table is the interaction of the two. 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 bachelors 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 5: Entrepreneurship

	All Counties			Hispanic Counties		
	(1)	(2)	(3)	(4)	(5)	(6)
Sole proprietor rate	-2.60	-8.42	-11.57	-19.58	-36.43***	-46.35**
	(7.52)	(7.38)	(9.40)	(12.49)	(12.20)	(18.24)
S-corp rate		23.81***			59.86***	
		(8.92)			(19.71)	
All establishments per cap			17.11***			39.03***
			(6.00)			(11.67)
Filed tax returns	2.47	3.01	-10.55	0.16	-0.57	-37.46*
	(7.63)	(7.69)	(9.54)	(12.30)	(12.24)	(19.16)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,001	3,001	3,001	1,501	1,501	1,501
Adjusted R^2	0.339	0.341	0.350	0.322	0.328	0.362

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 bachelors 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 6: Financial Development

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Banking establishments	0.17**						-0.07
	(0.08)						(0.10)
Savings banks		0.32					0.11
		(0.35)					(0.32)
Real estate			0.38***				0.25**
			(0.14)				(0.11)
Payday lending				0.41*			0.07
				(0.22)			(0.17)
All financial					0.14***		0.14**
					(0.05)		(0.06)
HH stock market participation						-0.60	
						(4.28)	
All establishments	0.02	0.03	0.03**	0.03**	0.02	0.03*	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,098	3,098	3,098	3,098	3,098	3,001	3,098
Adjusted R^2	0.342	0.340	0.343	0.342	0.346	0.339	0.348

This table investigates how access to financial institutions and financial development correlate with MLM incidence across the United States. The dependent variable is the MLM incidence rate scaled by 10,000 county inhabitants. The variable banking establishments is the number of banking institutions in the county per 10,000 inhabitants. Savings banks, Real estate, Payday Lending, and All financial, are the number of these establishments in the county in 2009 per 10,000 inhabitants, respectively. Household stock market participation is the per county rate of stock market participation using reported dividends from IRS tax data. All specifications control for the total number of establishments in the county as well as 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 bachelors 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	2,991	2,991	3,098	1,518	1,518	1,550
Adjusted R^2	0.346	0.345	0.341	0.324	0.320	0.326

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 bachelors 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 8: 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	3,098	3,098	3,098	3,098	3,098	3,098
Adjusted R^2	0.269	0.266	0.270	0.341	0.340	0.340

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 an 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 bachelors 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 9: 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	3,098	3,098	3,098	3,098	3,098	3,098
Adjusted R^2	0.374	0.374	0.406	0.400	0.407	0.401

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 an 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 bachelors 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 10: 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	334,622	313,640	334,622	334,622	334,622
Adjusted R^2	0.010	0.011	0.010	0.010	0.010

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 11: 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	334,622	313,640	334,622	334,622	334,622
Adjusted R^2	0.033	0.032	0.036	0.034	0.034

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.

Table 12: Direct Selling - Evidence from Survey Data

	(1) Direct selling	(2) DS main	(3) DS secondary	(4) DS intermediary
Hispanic	1.56	1.69*	2.11	4.65*
	(1.61)	(1.68)	(1.47)	(1.68)
White	1.85**	2.07***	2.08*	2.24
	(2.57)	(2.63)	(1.73)	(0.95)
Male	1.36**	1.54**	0.62*	0.37**
	(2.06)	(2.52)	(-1.78)	(-2.03)
Income tercile=2	1.17	1.36	1.60	1.40
	(0.89)	(1.46)	(1.48)	(0.64)
Income tercile=3	1.00	1.15	1.40	0.76
	(0.00)	(0.64)	(0.70)	(-0.41)
Age	1.01	1.00	1.00	1.02
	(0.24)	(-0.04)	(-0.02)	(0.31)
Age squared	1.00	1.00	1.00	1.00
	(-0.99)	(-0.88)	(0.07)	(-0.19)
Married	1.03	1.05	1.56	1.35
	(0.19)	(0.24)	(1.47)	(0.53)
College degree	0.83	0.74*	1.26	2.04*
	(-1.24)	(-1.70)	(0.63)	(1.78)
Multiple jobs	1.57**	0.64		
	(2.17)	(-1.40)		
Household buiness	3.82***	2.92***	5.75***	4.06**
	(7.15)	(5.02)	(6.08)	(2.48)
Family size	0.99	0.97	1.07	1.24
	(-0.22)	(-0.45)	(0.58)	(1.33)
Main job is self employment			1.51	3.94***
			(0.98)	(2.64)
Observations	3,800	3,800	3,800	3,800
Pseudo R2	0.08	0.07	0.11	0.16

This table investigates how individual level characteristics correlate with participation in direct-selling businesses. In Column 1, the dependent variable takes the value of one if the subject answered yes to the question *'on either your main job or a secondary job, do you do direct-selling to customers?'* In Column 2 (3), the variable indicates that the individual is involved with direct-selling in his or her main (secondary) job. Finally, in Column 4 the dependent variable takes the value of one if the individual answered yes to the following question: *'Do you work with an intermediary, such as Avon or Uber, in your direct-selling activity?'* The variables Hispanic and White define the race of the respondent, income terciles are the terciles of self-reported total income from all sources. The variable multiple jobs takes the value of one if individuals reported to work more than on job. Household business takes the value of one if the individual lives in a household where a member owners a farm or a business. Family size is the number of individuals in the household and main job is self employment takes the value of one when the individual is self employed. Standard errors are in parentheses. Coefficients are reported in odds ratios and ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 13: Direct Selling and Income - Evidence from Survey Data

	All income			Intermediary income		
	(1) Income	(2) Under 5k	(3) Under median	(4) Income	(5) Under 500	(6) Under med.
Direct selling	1.34**	0.62*	0.81	1.26	1.60	0.63*
	(2.36)	(-1.82)	(-1.29)	(0.90)	(1.49)	(-1.81)
DS intermediary	0.71	1.26	1.10	0.45	1.21	2.66*
	(-0.52)	(0.33)	(0.12)	(-1.55)	(0.35)	(1.65)
Demo controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,800	3,800	3,800	502	502	502
Pseudo R2	0.07	0.11	0.17	0.03	0.09	0.08

This table investigates how participation in direct-selling correlates with self-reported earned income. Columns 1 and 4 present ordered logit regressions where the dependent variable is the self reported income bracket associated with either *all income* in Columns 1-3, or *income from direct-selling intermediaries or alternative working arrangements*. We run logit regressions on indicator variables as dependent variables in Columns 2, 3, 5, and 6, which take the value of one if the earnings from all sources or direct-selling is less than $5,000; less than $500; or less than the median earnings. The variable *direct selling* takes the value of one if an individual is involved with any direct-selling in his or her occupation. The variable *DS intermediary* takes the value of one if the individual works with a direct-selling intermediary. In each regression we control for all covariates aside from income from Table 12. Standard errors are in parentheses. Coefficients are reported in odds ratios and ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

A Appendix Tables

Table 14: MLM Headquarters & Offices

	(1)	(2)	(3)	(4)
County with MLM office	4.91***		4.95***	4.96***
	(1.32)		(1.33)	(1.35)
County with main MLM office		3.80**	4.45**	4.45**
		(1.74)	(1.82)	(1.85)
Office county connectivity				0.48
				(4.41)
Controls	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes
Observations	2,741	2,741	2,741	2,741
Adjusted R^2	0.369	0.368	0.369	0.369

This table investigates how MLM headquarters and office location influence MLM incidence across the United States. The dependent variable is the MLM incidence rate scaled by 10,000 county inhabitants. 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 bachelors 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 15: Average FTC Refund and Household Income

	(1)	(2)
Log median household income	0.16***	0.08
	(0.03)	(0.05)
Controls	No	Yes
State Fixed Effects	Yes	Yes
Observations	2,909	2,649
Adjusted R^2	0.050	0.095

The dependent variable is the Log Average FTC refund. Column 1 does not include control variables. Column 2 includes controls 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 bachelors 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.

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