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Reaching the Hard to Reach with Intermediaries: The Kansas City Fed's LMI Survey

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Abstract:

Reaching hard-to-reach individuals is a common problem in survey research. The low- and moderate-income (LMI) population, for example, is generally hard to reach. The Kansas City Fed's Low- and Moderate-Income Survey addresses this problem by sampling a database of organizations to serve as proxies for the LMI population. In this paper, I describe why the LMI population can be hard to reach. I then explore potential problems with using a nonrandom survey sample and address the empirical validity of the Kansas City Fed's LMI Survey. I compare results from the survey using the standard sample to results from the survey using a random sample. I find that the results of the surveys using the standard and random samples are not significantly different and conclude that the use of a nonrandom sample is not a significant problem for the LMI Survey. I find that the series of responses from the LMI Survey are correlated with the things they should be correlated with, suggesting that the survey is empirically valid and does a good job of measuring economic conditions in LMI communities.

Reaching the Hard to Reach with Intermediaries: The Kansas City Fed's LMI Survey

1.   Introduction

Reaching hard-to-reach individuals is a common problem in survey research. The low- and moderate-income (LMI) population, for example, is generally hard to reach. The Kansas City Fed's Low- and Moderate-Income Survey addresses this problem by sampling a database of organizations to serve as proxies for the LMI population. In this paper, I describe why the LMI population can be hard to reach, explore potential problems with using a nonrandom survey sample, and address the empirical validity of the survey.

The Federal Reserve Bank of Kansas City initiated its Low- and Moderate-Income Survey in the first quarter of 2009.[1] A number of other Federal Reserve Banks have followed suit with similar surveys. The purpose of the survey is to collect information about economic conditions in low- and moderate-income (LMI) communities; specifically, job availability, housing affordability, and access to credit. There are also questions that seek broad assessments of the LMI community. One asks for an overall assessment (better, worse, or about the same), while another asks about the demand for services provided by social and community organizations.

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[1]Surveys abound at central banks. Examples at the Federal Reserve Bank of Kansas City are surveys of manufacturing, the services industry, the energy industry, and the retail sector. Most other Federal Reserve Banks have similar surveys. Other examples include the Federal Reserve Board's Senior Loan Officer Opinion Survey, the Federal Reserve System's Small Business Credit Survey, the Federal Reserve Bank of New York's Survey of Consumer Expectations, and the Bank of Canada's Business Outlook Survey. The surveys provide value in a number of ways (Martin and Papile, 2004). Most importantly, they provide more timely data than official statistics, which typically lag the time the data were collected by a quarter or more. These surveys also provide a great deal of information that is not available in official statistics. Some of the information is objective data collected from individually crafted questions, while valuable anecdotal information also is collected via surveys.

For the LMI Survey, ideal respondents are hard to reach. They are hard to reach in a couple of ways. First low-income people are generally harder to reach than are higher-income people. Secondly, even if a reasonable number of low-income people can be reached, it would be difficult to reach people who have the necessary information and experience to answer the questions in our survey accurately. For questions about the availability of jobs, we would need survey respondents who are seeking employment. For questions about affordable housing, we would ideally question people who are actively seeking housing. We would need people who are seeking a loan to address access to credit, and so on.

Because LMI individuals and households with the characteristics we require are rare and hard to reach, we instead survey community service establishments. Specifically, our survey targets organizations that have regular, direct contact with LMI people and communities. The assumption underlying this approach is that, having directly interacted with the LMI on a regular basis, these organizations would be able to translate the views of LMI people to the survey. In addition, the survey respondent may include his or her own assessment of conditions based on what has been gleaned from LMI clients.

The paper proceeds as follows. Section 2 explains why LMI people often are difficult to reach with surveys and are especially difficult to reach with our survey. Section 3 discusses the Kansas City Fed's LMI Survey in detail. Section 4 provides analyses that address the nonrandom sampling in the survey. Section 5 explores the empirical validity of the LMI Survey by comparing results to a number of external benchmarks. Section 6 provides conclusions.

2.   Issues Reaching the Low-Income Population

Hard-to-reach populations can be excluded or drop out at multiple points in the survey process (Stoop, 2014; Groves, 1989). The target population may exclude sub-populations, perhaps due to the cost of data collection. For example, migrant workers or the homeless may be overlooked in population counts. More people may be lost in choosing the sampling frame and mode. For example, telephone surveys based on lists of landline telephone numbers likely would miss mobile-only households. Nonresponse may then further undermine full representation. For example, non-English speakers likely would not respond to a survey written in English. Others may be unable to respond because of a lack of information adequate to answer the survey questions.

In conducting our survey, we need to balance twin aims of representativeness and cost-effectiveness (Faugier and Sargeant, 1997). For us, the largest cost associated with reaching hard-to-reach respondents is time. The Kansas City Fed publishes a biannual report, *LMI Economic Conditions*, using results from the LMI Survey, and the report is typically released within two months of the survey period. The short timeframe is necessary if we are to provide timely information to Fed management, policymakers, community organizations, and the public.

If the survey were to question LMI households directly, headline results could take months to release. Some private and national surveys, such as the Census, can take anywhere from several months to several years to produce headline results. Many other national surveys which have probability-based, representative samples, such as the Current Population Survey and the American Community Survey, have considerable resources to produce timely headline results.

It is not only low-income people *per se* who are difficult to reach, but especially specific subgroups within the population of low-income people. Abbott and Compton (2010) suggest that, at least in population counts, the hard to locate are often people claiming income support, young people, minorities, those with lower relative house values, and those living in dense (i.e., multiunit) dwellings. These characteristics were identified by "area level" logistic regression in planning the 2011 UK census (see also ONS, 2009). All of these groups are more common in low-income populations than in higher-income populations.

Through anecdotal evidence, Abbott and Compton also identify illegal immigrants, boarders/lodgers, the homeless, those with disabilities, and institutionalized populations (i.e., in the armed forces or in prison; see also Abrams, 2010).[2] Nicaise and Schockaert (2014) identify single parents, immigrants, tenants, and inner city inhabitants as hard-to-reach. Glasser et al. (2014) highlight those whose residences are in flux as hard to reach, particularly the homeless, as well as renters, young men, and immigrants. Bates et al. (2008) examined reasons for refusing to participate in a survey once contacted. They identify those in multi-unit structures, as well as those living in central cities (see also Pottick and Lerman, 1991) and/or those with language barriers. Again, all of these groups are more common in low-income populations than in higher-income populations.

Issues Making the LMI Hard to Survey

Changes in residence make potential survey respondents difficult to locate, and low-income people typically change residence much more often than higher-income people (Newman and Owen, 1982; Scanlon and Devine, 2001). In particular, low-income people are much more commonly faced with "involuntary" mobility, usually over short distances (DeLuca et al., 2011).

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[2]Also identified were Gypsies/Travelers, those in gated communities, caravan dwellers, boaters, and visitors.

These involuntary moves may arise from gentrification, neighborhood disinvestment, evictions, poor housing quality, or domestic situations, among other reasons.

In 2016-2017, 17.4 percent of those with income below the poverty line changed residence, compared to 10.1 percent of those living above the poverty line (U.S. Census Bureau, 2017a). Almost two-thirds of the moves were within the same county. Of those living between 100 percent and 150 percent of the poverty line, 13 percent moved.

Families in the Moving to Opportunity program, which offered opportunities to move from traditional public housing to higher-income neighborhoods, averaged four address changes in the 5-year period preceding the final research interview (Hudson et al., 2012).[3] Many of these faced significant housing instability, including doubling up with friends or homelessness. The homeless are a particularly mobile, hard-to-reach population that is low-income (Glasser et al. 2014).

Time is a clearly a factor in unit nonresponse. If there are desirable alternative uses of time upon initial interaction with a survey interviewer (or in our case, an emailed survey request), we might expect the subject to attempt to terminate the interaction (Groves and Couper, 1996). If few desirable alternative uses of time are available, the subject will attempt to clarify the purpose of the interaction (in our case, the email). The relationship between unit nonresponse and time has been well documented in the literature. For example, among those refusing to participate in the National Health Interview Survey (NHIS), three of the top five reasons for refusing to participate were time-related; specifically, "too busy," "interview takes too much time," and "scheduling difficulties," with "too busy" being the first. (Bates et al., 2008, Table 1). Overall refusal rates (interim or final interviews) were 23.9 for "too busy", 11.9 for "too much

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[3]For details on the Moving to Opportunity demonstration, see Sanbonmatsu et al., 2011.

time," and 8.6 percent for "scheduling." Morton-Williams and Young (1987) have similar findings for their survey of "issues facing Britain." Among the most reluctant to participate in the survey were those who were "busy at the moment" (p. 43). "Length" and "too busy in general" were also significant factors in reluctance to complete the interview.

One group that often struggles with time is single parents, who are also much more likely than married couple families to be low income. Among those in poverty, 51.3 percent of families are headed by a female householder with no husband present, compared to 19 percent in the population as a whole (U.S. Census Bureau, 2017b).[4] Families with a single male householder also are moderately more prevalent in poor families at 10.9 percent, compared to 7.7 percent in the population at large. The remaining 37.8 percent of families in poverty are headed by married couples. A number of ethnographic studies have documented the time constraints faced by single parents (see, e.g. Seefeldt and Sandstrom, 2015 and Roy et al., 2005). Time can be thought of as an additional dimension of poverty, as restricted time reduces household production of nonmarket goods (such as preparing meals, cleaning, etc.) (Vickery, 1977; Burchardt, 2008; Harvey and Mukhopadhyay, 2007).

Some may not be able to participate in the survey because of a language barrier. Bates et al. (2008) found language barrier to increase refusal to participate in the NHIS by 63 percent. The Program for the International Assessment of Adult Competencies suggests that 9.5 percent of Americans do not speak English (Van de Kerckhove et al., 2013). Non native-born residents make up 16.2 percent of the poor population, compared to 11.1 percent of the population at large (U.S. Census Bureau, 2017b). While many immigrants speak English very well, and some come from English-speaking countries, a significant fraction would have difficulty responding to a

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[4]A family is a group of two or more related people who are residing together.

survey written in English. A slim majority of non-native residents in the U.S. are native to Latin American countries, where Spanish is generally spoken. Feskens et al. (2007) suggest that those with language barriers may be just as likely to participate in a survey if reached by someone who speaks their language. While we could address this problem in the survey design by translating the survey questionnaire into Spanish, we would not be able to provide a survey in the numerous other native languages spoken in the U.S.

Among non-natives in the U.S., those who are not citizens can be especially hard to reach, particularly if they are undocumented. Immigrants in general have many of the characteristics of other hard to reach groups, including high rates of mobility, irregular housing arrangements, and low levels of education and income. (Massey, 2014). In addition, undocumented immigrants often are mistrustful of authorities and are stigmatized as a group. They may make efforts to be as invisible as possible, making them difficult to locate. In 2016, 13.6 percent of the population living in poverty were noncitizens, compared to 8.3 percent of the resident population at large. Of course, many noncitizens are documented with visas or permanent residence.

Another difficult to survey group is the disabled, particularly those who have mental disabilities. These difficulties may make it difficult for them to complete the survey. In 2016, 17.9 percent of those living in poverty had some kind of disability, compared to 7.7 percent of the general population (U.S. Census Bureau, 2017a).

The method of communication can intensify problems surveying the hard-to-reach. Sampling emails is not plausible for low-income people as a population. Email lists generally are confined to member lists and contact databases. Telephone surveys are increasingly difficult for all groups (Miller, 2017), but particularly for low-income people. In the latter half of 2016, 54

percent of U.S. households did not have a landline phone (Blumberg and Luke, 2017). Of these, 50.8 percent were wireless only, while 3.2 percent were phoneless. Difficulty in reaching people by landline is more pronounced for those with low incomes. Specifically, 66.3 percent of adults living in poverty and 59 percent of adults in near poverty live in households with only wireless phone service. An additional problem with surveying landline-only households is that some households with landlines rely on wireless phone for all or almost all of their calls and therefore cannot be reached by landline. Specifically, 38 percent of households with both landline and wireless service make and receive all or most all of their calls on their wireless phones. A significant problem facing MTO final interview surveyors was that "difficult-to-reach" respondents often did not have a phone or had very few cell phone minutes (Gebler et al. 2012)."

Cost Concerns

Costs are always a consideration for a survey, and our resources for the LMI Survey are limited. As an example of how costly surveys can be, consider the Moving to opportunity program and study. The final interview survey effort associated with the Moving to Opportunity program highlights the expense of tracking down and interviewing hard-to-reach respondents, particularly when meeting a high standard for effective response rate (Gelder et al., 2012). The survey was led by the Institute for Survey Research (ISR) at the University of Michigan. MTO costs per final impact interview were about $500 at the beginning of survey fielding in June 2008, but climbed to $1,600 when survey fielding was finalized between December 2009 and April 2010. Part of its "end game strategy" to reach the hardest to reach (those interviewed after having met a 75 percent effective response rate) was to offer finders fees to those who helped to locate a prospective respondent. These increased from $5 to $10 initially to $50 near the end of

the project. Interview payments increased from $100 at the beginning of the end game effort to $200 by the final two months of the collection effort.

Those meeting the criteria for being included in the sample likely comprise a small subset of the total LMI population, and thus, a very large population relative to the target population would need to be screened. For example, to be adequately informed about job availability, one would likely have to be actively seeking employment. To be adequately informed about the availability of affordable housing, one would have to be in the market for housing, and so on. There is little difference in cost between a screening interview (by email) and a final interview (by email), so the total cost of screening would be several-fold higher than the cost of the final interview (Tourangeau, 2014). For us, this cost comes in the form of turnaround time for the final survey.

3.   The Kansas City Fed Low- and Moderate-Income Survey

The genesis of the Kansas City Fed's Low- and Moderate-Income (LMI) Survey was a desire to stay abreast of economic conditions in LMI communities. Originally the plan was to collect published statistics on LMI people, households, and communities and to compile them into a regular report. However, upon searching, we found very little information and few statistics specific to this segment of the population. We then made the decision to collect relevant data ourselves through a survey.

The Kansas City Fed's LMI Survey commenced in the first quarter of 2009. Surveys were distributed quarterly until 2014, when we began to distribute surveys biannually. The survey is in some sense a panel survey in that the survey is distributed to a nearly identical sample from period to period. But it also has characteristics of a repeated survey in that

organizations drop in and out of the survey and survey respondents may respond sporadically to the survey.

Mode

The LMI Survey is email–based. On the first Monday of January and July, invitations to participate in the survey are sent to prospective respondents with a unique URL. The unique URL allows us to track individuals' responses over time. Once recipients click on the URL, they are brought to a point–and–click survey. The survey is open for two weeks. Reminder emails are sent one week before the closing date and one day before the closing date. A large majority of surveys are completed on the first day of the survey or on the days when reminders are sent out. Recipients are given the option of opting out of future survey requests.

We use Oracle's RightNow platform to administer the survey and to collect and compile the response data.[5] RightNow, which is part of Oracle's cloud services, is used by the Kansas City Fed primarily for customer relationship management. But the platform has a component designed specifically for administering surveys.

The email/internet mode has several advantages over telephone and mail modes. Email surveys are more cost effective, can be transmitted quickly, and can be turned around quickly. Our RightNow survey platform offers an advantage because our prospective survey respondents are already loaded into the database. While we manage our contact list to make additions, subtractions, and corrections to contact information, the distribution of invitations and reminders and the collection and compilation of survey response data are fully automated.

Web-based participants are able to reread their responses, making their responses better thought out and less spontaneous (Comley, 1997; Coderre et al.)

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[5]The discussion of Oracle RightNow should not be considered an endorsement of the product.

Sampling Frame

The purpose of the survey is to get perceptions of economic conditions in LMI communities, but as documented above, LMI individuals and households can be difficult to reach. To address this problem, we use establishments as proxies for LMI people and households. Specifically, our survey targets organizations that have regular, direct contact with LMI people and communities. Typically, the survey is sent to the executive director of an organization, but the executive director is free to pass along the survey to whomever is most qualified to complete it. The organizations largely provide social services and community outreach in LMI communities and are involved in a wide variety of sectors, including basic needs (e.g., food banks or utility assistance), health (e.g., clinics or advocacy groups), education (e.g., charitable preschool programs or parenting support), self-employment support, and others.

The sample is drawn from a contact database managed by the community development function at the Federal Reserve Bank of Kansas City. Contacts are entered into the community development database upon any interaction with the Kansas City Fed, such as registration for a meeting or event or when exchanging contact information. The sample is best characterized as a "convenience sample."[6] That is, members of the sampling frame meet specified, practical criteria. For us, the chief practical criterion is accessibility.

The database provides a number of benefits in addition to accessibility. First, we can use the database to readily identify organizations that serve LMI populations. Second, the database, which is actively managed and updated, provides email addresses that are unlikely to be outdated

[6]In the Federal Reserve System, most surveys are not random surveys, but efforts are made to make them regionally representative and representative of the regional industrial make-up. Often purposive sampling is used to achieve these goals. There are a number of methods for purposive sampling, but in all cases they involve a deliberate choice of a participant due to the qualities the participant possesses (Etikan et al., 2015). For surveys of business conditions, efforts are made to ensure that all industries, firm sizes, and geographies are represented in proportion to their weight in total economic activity. The New York Fed's Survey of Consumer Expectations is an exception in that it is a nationally representative probability-based sample.

or inactive; and when they are, we are usually able to track down the individual's current email address or the email of the address of the person currently in that position, or both. Third, survey emails from known sources are less inhibiting and have a greater likelihood of response (Michaelidou and Dibb, 2006). Each of our outreach staffers covers a geographic portion of the Kansas City Fed District. The email survey invitations arrive as if sent individually by the local outreach staffer, and the salutations are personalized. The database sample also suits our research objectives. The goal of the survey is to use responses to help understand unobserved phenomena. We doubt there is a significant systematic difference in those who are and are not in the contact database. However, to the extent there are systematic differences, the effect is somewhat muted because we analyze a time series of responses using a rolling benchmark (see below).

Contacts are vetted to ensure that they have regular, direct contact with the LMI community. For example, contact information for a number of Community Reinvestment Act (CRA) compliance officers at commercial banks and credit unions are recorded in the database, but they typically work with establishments and therefore usually do not interact with LMI people directly as part of their work. Thus, CRA officers are excluded from the survey pool.

Contacts in the database are from a restricted geographic area. The Kansas City Fed covers a seven-state area incorporating Colorado, Kansas, the western third of Missouri, Nebraska, the northern half of New Mexico, Oklahoma, and Wyoming. Survey invitations are sent only to those in the database who reside in the district.

In July 2017, survey invitations were sent to 4,585 contacts, of whom 397 responded (8.7 percent). A regulatory issue required a culling the sample for the January 2018 survey. This change reduced the sample to 2,607 of whom 219 responded (8.4 percent).

Questionnaire Design

We designed the questionnaire to solicit input sufficient to adequately assess economic conditions but to take less than 5 minutes to complete, depending on the breadth of efforts to provide free-response comments (see below). The brevity of the survey is intended to maximize the probability that the survey will be started and completed (see Marcus et al., 2007; Galesic and Bosnjak, 2009); minimize the probability that respondents will get fatigued, disinterested, or distracted (see Galesic and Bosnjak); and to promote thoughtful responses.

The survey consists of seven three-part questions. For each of the seven components, survey respondents are asked to assess conditions compared to the previous quarter and year and to make a projection of conditions for the next quarter. The questions offer three possible responses: better (or higher), worse (or lower), or about the same. The response structure is therefore exhaustive and mutually exclusive. Moreover, the format of the questions does not require the respondent to translate an estimate or judgment into a numerical answer. For example, the first question asks about the demand for services provided by the respondent's organization. We could have asked how many clients were served in the previous quarter and year, but that format could lead to difficulties such as rounding, forgetting, or telescoping, if the answer were encoded in the first place (Tourangeau and Bradburn, 2010).

The question ordering reflects our effort to keep the respondent engaged and committed to completing the survey. The first question is the simplest, most objective question in the survey (full questionnaire in appendix):

> 1. How did the demand for your services change during the past quarter compared to:
>
> > a) the previous quarter? _____ increased _____decreased _____no change
> > b) the same period a year ago? _____ increased _____decreased _____no change
> >
> > Next quarter, how do you expect the demand for your services to change?
> > _____ increase _____decrease _____no change

Have you made any recent efforts to further market your services? ____ Y ____ N

Have there been any unusual events (*e.g.*, weather related) that have affected the demand for your services? ____Y ____N

If yes, please briefly explain _____

Unlike the others, this first series of questions has five components to ensure clarity. A cold snap likely would lead to increased demand for utility assistance, but that increase would not reflect a change in the economic pulse of the community. Similar reasoning is behind the question on marketing campaigns.

Remaining questions ask about job availability, access to credit, availability of affordable housing, and an overall perception of economic conditions (better, worse, or about the same). The last two three–part questions ask about funding for the respondent organization and its nonfinancial capacity, such as the availability of property and volunteers.

Survey respondents also are provided with a box for each three-part question in which to make comments and a box at the end of the survey for general comments. The comments are used in the report to give the survey results context. Roughly one-third to one-half of respondents make comments, depending on the question. The survey instrument also provides flexibility to ask special questions each survey period. Typically, these questions are open-ended. As an example, our July 2017 survey asked respondents what they felt was the right statutory minimum wage and how they think higher minimum wages would affect employment and the overall financial well-being of LMI people as a community.

The first step in designing the questionnaire was to get input from internal community development outreach staff and external community development stakeholders about what they felt would be the most important economic metrics to follow. We used this input, along with our own thoughts as economists, to develop the questions. Survey prototypes were sent to several of

our external community stakeholders for pretesting. We received critical feedback from the respondents along with their survey responses.

Analysis of Survey Responses

We use diffusion indexes to track economic conditions in LMI communities over time. A diffusion index provides a balance of opinion. It is constructed by subtracting the share of respondents reporting conditions are worse (e.g., jobs are less available or demand for services is higher) from the share reporting that conditions are better (e.g., affordable housing is more available) and adding 100. Thus, the diffusion index takes a value from 0 to 200, where 100 is neutral, or balanced. A neutral reading of the diffusion index means that the share responding "better" was equal to the share responding "worse," with the remainder responding "about the same." If the index exceeds 100, the balance of opinion says that economic conditions are improving, while an index below 100 indicates a balance of opinion that says economic conditions are deteriorating. A value below 100 indicates that conditions are deteriorating even if the value is higher than it was in the previous survey.

We create a diffusion index for each of the 21 survey questions (excepting the two follow ups in the first set of questions). Figure 1 shows the diffusion indexes for job availability compared to the previous quarter, job availability compared to the previous year, and expectations for job availability in the ensuing quarter. The survey began during the depths of the Great Recession, and then the balance of opinion was decidedly negative. It remained negative, though climbing higher, until 2012. Since 2012, the balance of opinion has mostly remained in positive territory.

Figure 2 shows diffusion indexes for demand for services (greater demand is associated with a lower index value), affordable housing, access to credit, and an overall assessment of

economic conditions relative to the previous year. All of the indexes have remained below neutral for the life of the survey. Survey comments reveal a number of reasons why the balance of opinion on economic conditions in LMI communities remains negative as the national economy booms.

First, in the face of higher rents and house prices and a dearth of new construction, affordable housing is becoming less available. While rising home prices generally are an indicator of health in real estate markets, they are a problem in LMI communities where households of limited means are seeking affordable homes to purchase. Further, even if subsidized housing units were being built at higher rates—and they are not—rising rents have made market-rate housing unaffordable for many LMI households, especially in the multifamily sector.

Second, long-term unemployment has remained stubbornly high, even as unemployment rates have declined sharply. Long-term unemployment can cause the demand for services to increase even as the economy is recovering (Edmiston, 2018). With prolonged unemployment, one typically exhausts any unemployment benefits (which most hourly workers do not receive) or savings that may have been accrued (which is usually negligible for LMI families). The long-term unemployed will eventually turn to social and community services (as well as public assistance). Still, at this point in the recovery, while we might expect the demand for services to remain elevated, it should not be increasing. A potential complicating factor is that LMI Survey respondents may stress conditions for the poorest of their clients. A tendency to stress conditions of the poorest also may explain consistently low values for the overall assessment question.

The textual analysis of the comments largely amounts to a careful reading of the comments and a grouping of comments into themes. We then identify themes that explain recent

patterns in survey responses. We frequently create word clouds to assist us in identifying these themes and may include the word clouds in our biannual report. Figure 3 shows a word cloud for comments about job availability from our most recent survey.

4.   Tests of the Non-Probability Sample

Sampling Error

An important issue to consider as part of our evaluation of the empirical validity of the survey is the quality of the sampling design. We would like to know how representative our sample is compared to the population of community-based organizations that serve LMI people in the Tenth Federal Reserve District.

There is a large variety of random sampling methods (Frankel, 2010). What these random sampling methods have in common is that there is a known, nonzero probability of each element in the population frame being sampled. The primary issue facing us in our sample design is the lack of a population frame from which to draw a random sample. Our sample is drawn from a contact database and therefore is not probability-based. There is potential for coverage error that could be avoided with a probability-based sample.

To identify and address potential problems arising from the use of a nonrandom sample, we compare results from our survey using our standard sample to results from our survey using a random, or near random sample. We call the random sample a parallel sample. We conducted parallel surveys in January 2018 by distributing the LMI survey to the parallel sample simultaneously with our standard survey sample.

Our parallel sample was drawn from the Guidestar database. Guidestar is a nonprofit organization which collects data on IRS-registered nonprofits. Guidestar collects publically available data from the IRS for virtually every community-based organization in the country. Guidestar categorizes community organizations by National Taxonomy of Exempt Entities (NTEE) codes, IRS subsection, affiliation type, and whether the organization was revoked from the IRS, is defunct, or merged with another organization.

A potential pitfall of the Guidestar database is that a majority of organizations lack contact information in their profiles. We do not have the resources to draw a probability-based sample and research contact information for each element in the sample. What we can do, however, is to draw a sample from the Guidestar database of community-based organizations that do have contact information in their profiles. Thus, implicit in our comparison of samples is an assumption that organizations with contact information are not systematically different from organizations without contact information. This assumption is not testable with available resources.

For a number of legal, ethical, policy, and vendor issues, we are unable to continuously use the Guidestar database as our sampling frame. The primary problem is that the survey respondents need to opt *into* the survey pool. Our contact with the Guidestar sample was a one-time contact, which does not need to meet the same requirements as a sample we intend to use in a continuous fashion. But there are other reasons to continue using our standard sample as well. First, we trust the members of our contact database and can validate their suitability for the survey and their contact information. Second, we use the survey in part to maintain relationships with our contacts and partner organizations. Finally, cost is a factor.

We drew a simple random sample from organizations in the Guidestar database that have

contact information. Each of the N elements in the population frame had an equal probability $1/N$

of being selected. We collected 3,178 contacts for the parallel sample. In cases where a survey

contact appeared in both samples, we surveyed them once but included the results in both sets of

responses. We performed a number of tests to judge differences in responses between our

standard survey and the parallel survey.

Figure 4 shows the standard and parallel survey responses, along with bootstrap standard

errors (10,000 replications). The baseline responses (actual responses) generally are close

together for the economic variables and have confidence intervals that intersect. The exception is

the demand for services year-over-year comparison. Table 1 provides t-statistics for the

difference in means for these variables. The standard and parallel responses are not statistically

different for economic variables, again with the exception of the demand for services year-over-

year comparison.

Responses for questions about organization funding and capacity conditions for the two

samples were very different, however. Specifically, respondents in the parallel survey reported

systematically higher numbers for funding and capacity than did respondents in the standard

survey. The t-statistics show that the baseline responses are statistically different. Given the

closeness of the responses for economic variables, we do not believe that differences in

responses on funding and capacity are due to sampling error. Rather, we expect that some of the

respondents in the standard sample; specifically, frequent respondents, have a better sense of

historical levels of funding and capacity having completed the survey several times. Figure 5

provides some evidence of this phenomenon, showing that the responses of infrequent

respondents tend to be higher than those of frequent respondents. Still, we do not use the survey

results to make inferences about funding and capacity in this paper but instead focus entirely on the five economic constructs. The remainder of the paper considers only the economic variables.

Scatter plots visually demonstrate that the standard and parallel samples are relatively close to the 45-degree line, which represents perfect equality between the paired samples (Figure 6). In general, the standard sample gives slightly higher valuations of the balance of opinion, but these differences generally are not statistically different from zero. A series of t-tests for differences in means failed to reject the null of no difference at the 0.01 significance level for all survey questions other than the year-over-year comparison of demand for services (Table 1). The slopes of the regression lines in Figure 6 are not statistically different from unity at the 0.05 significance level (Table 2). Correlation coefficients are all 0.94 and greater. Kolmogorov-Smirnov tests failed to reject the null.[7]

Reliability

Reliability refers to the consistency of repeated survey measurements (see Alwin, 2010). It is the degree to which the variance of the measure is due to systematic sources rather than noise (Bohrnstedt, 2010). Estimating reliability from information collected within the same survey is difficult (Alwin, 2010). It is virtually impossible to replicate questions, and survey respondents likely would be put off by repetitive questions. Moreover, memory of previous answers would likely inflate the correlations between answers.

We try to get a sense of the reliability of our survey by comparing our results to those of other Federal Reserve Banks that use or have used an identical survey questionnaire. If the surveys generate similar values, there is evidence of reliability in the survey instrument. The comparability can be determined by correlations or tests of comparison among distributions. If

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[7]Small sample sizes give the Kolmogorov-Smirnov test limited power to reject the null (Mendes and Pala, 2003).

the results are inconsistent, however, then the reliability of the survey instrument is ambiguous. Survey results may differ because they are not reliable or they may differ because the conditions they measure—in our case economic conditions—differ. For example, even if the survey is reliable, results will be significantly different if one region's economic growth is strong and the other economy's economic growth is weak.

Figure 7 shows survey responses for the Federal Reserve Banks of Boston, Dallas, Kansas City, and Philadelphia, all of which use the Kansas City Fed survey questionnaire. All of the Reserve banks collect the survey sample using the Kansas City Fed's method; that is, a contact database.

Comparison statistics are provided in Table 3. For Boston and Philadelphia, Kolmogorov-Smirnov tests fail to reject the null that the series come from the same distribution as Kansas City. For Dallas, however, we can reject the null. The correlation coefficient for Dallas and Kansas City is 0.94, however, which suggests that they move nearly in tandem. The distributions are different because the Texas economy performed very well during the Great Recession and early aftermath compared to most other regions of the country, including the 7-state Kansas City region (Wilkerson, 2009; Connaughton and Madsen, 2012). This reality raises the mean for the Dallas survey. The variances are close to equal for Kansas City and Dallas at 11.3 and 11.9, respectively. Significant positive correlation is also evident for Boston and Philadelphia when paired with Kansas City.

As an additional reliability test, we compute Chronbach's alpha for the Kansas City, Dallas, and Philadelphia series (Bohrnstedt, 2010). Chronbach's alpha is a measure of the interrelatedness of the survey responses and is a lower bound for reliability. It refers to the extent

that the variance is due to systematic sources rather than noise. Ranging between 0 and 1, the

higher is α, the more reliable the survey. The calculation is

(1) $\alpha = \left(\frac{k}{k-1}\right)\left(1 - \frac{\sum_{i=1}^{k} \sigma_{x_i}^2}{\sigma_x^2}\right),$

where k is the number of items, x_i is an individual item, and $x = \sum_1^k x_i$.

For the three surveys, looking at the quarter-over-quarter job availability question, $\alpha = 0.910$. By most standards, 0.910 is considered high and indicative of a reliable indicator

(Nunnally, 1978; research cited in Tavakol and Dennick, 2011).

5.   **Empirical Validity Measures**

In this section, we evaluate the empirical validity of our survey measures by comparing

them to external data, usually government-produced statistics. The comparisons are evaluated by

charting the data and computing correlation coefficients.[8]

Job Availability

A question in the LMI Survey asks respondents whether jobs have become more

available, less available, or about the same. The resulting diffusion indexes are termed LMI Job

Availability Indexes. Respondents are asked to complete this evaluation compared to the

previous quarter and previous year. They are also asked about their expectations for the

following quarter. If the LMI Job Availability Index is an empirically valid measure, it should be

correlated with employment growth. One way to test the empirical validity of this measure is to

compare the balance of opinion on job availability against employment growth over the past year

for LMI workers. Although there are no statistics on employment growth for LMI workers, and,

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[8]Differences in means and variances precluded the use of most other tests comparing distributions.

indeed, income and employment are very difficult to disentangle, we can use proxies that we feel represent employment growth for LMI workers.

Low- and moderate-income people are presumed to earn relatively low wages, which are generally associated with low-skill jobs. Two industries with especially low wages and skill requirements are accommodations and food services, which paid a median wage of $10.57 in 2017 ($21,140 annually, full-time), and retail, which paid a median wage of $11.96 ($23,920 annually, full time).[9] These jobs generally do not require a formal education credential or previous work experience and rely on short-term on-the-job training.[10] By comparison, the overall median wage is $18.12, and for management occupations, the median wage is $49.32. The poverty threshold in 2017 for a family of three with two related children was $19,749, and 80 percent of median income for the U.S. was $44,258.

Figure 8 shows the year-over-year LMI Job Availability index along with year-over-year employment growth in accommodations & food services and retail occupations. The data chart very closely with similar patterns. The correlation coefficient for the LMI Job Availability Index and retail employment is 0.77. For accommodations & food services, the correlation is 0.86. These calculations provide evidence that the job availability index is adequately assessing job opportunities for LMI workers.

In addition to occupation classes, we can compare LMI job availability to *industry* employment; specifically, sectors that typically employ low-skill, low-wage workers. An advantage of these data is that they can be aggregated to the level of Federal Reserve districts. Examples of these industries are leisure & hospitality and retail trade. The average hourly wages

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[9]Data on median wages are available in Occupational Employment Statistics, U.S. Bureau of Labor Statistics. For these calculations, full-time workers are assumed to work 40 hours per week for 50 weeks per year.
[10]Data on job requirements are found in the *Occupational Outlook Handbook*, U.S. Bureau of Labor Statistics.

in 2017 in the leisure & hospitality and retail trade industries were $15.44 and $18.16,

respectively, compared to an economy-wide (private sector) average wage of $26.33.[11] Figure 9

shows the LMI Job Availability Index (right axis) along with employment growth rates for the

leisure & hospitality and retail trade sectors and also the service sector more broadly.

Employment growth in these low-wage industries moves closely with the LMI Job Availability

Index. The correlation coefficients for leisure & hospitality and retail trade are 0.91 and 0.78,

respectively. The correlation coefficient for job availability and the services sector as a whole is

0.88.

Education provides another proxy for low- and moderate-income. Education and income

are highly correlated. An individual with no high school diploma had median usual weekly

earnings of $520 ($27,040 annually) in 2017, compared to $712 for those with a high school

diploma ($37,024 annually) and $1,173 for those with a college degree ($60,996 annually).[12] We

compare the LMI Job Availability Index with employment growth by level of education

attainment. Job availability tracks closely with employment growth for those with less than a

high school education and those with a high school education (Figure 10). The correlation

coefficients are 0.70 and 0.83, respectively.

Black and Hispanic workers are disproportionately low- and moderate-income. In the

first quarter of 2018, median usual weekly earnings for all workers was $881, but for black

workers was $696, and Hispanics $675. The LMI Job Availability Index tracks closely with

employment growth for minorities (Figure 11). The correlation coefficient for the LMI Job

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[11]U.S. Bureau of Labor Statistics, Establishment Survey. These wages are not comparable to occupation wages stated previously. Average salaries are higher than median salaries because the distribution of wages is skewed to the high-end. Further, industry employment includes those in management positions as well as those in low-skill, low-paying jobs, which make up the bulk of jobs in these industries.

[12]U.S. Bureau of Labor Statistics, "Unemployment rates and earnings by educational attainment, 2017," March 27, 2018. Available at https://www.bls.gov/emp/ep_chart_001.htm/.

Availability Index and black employment growth is 0.88. For Hispanic workers the correlation coefficient is 0.80.

Affordable Housing

LMI Survey responses are used to provide an LMI Affordable Housing Index. The associated question asks if the availability of affordable housing is higher, lower, or about the same. Affordable housing has a specific definition. Housing is affordable if expenditure is less than 30 percent of income.

One way to empirically evaluate the validity of the LMI Affordable Housing Index is to compare it to trends in rent. As rents increase, a smaller share of the housing stock would be affordable by definition. Figure 12 shows the LMI Affordable Housing Index and Fair Market Rent for the U.S. Fair Market Rents are set at the 40th percentile within the distribution of market-rate rents. Fair Market Rents are calculated annually by the U.S. Department of Housing and Urban Development for use in setting payment standard amounts for the Housing Choice Voucher program (Section 8). Because Fair Market Rent is set below median rent (by 10 percentage points), it better reflects the rents that lower-income households actually pay than median or average rents. If renters were to select units in the same rank order as their incomes, households paying Fair Market Rent would be just on the cusp of the LMI threshold, or 80 percent of area median income. The correlation coefficient for the LMI Affordable Housing Index and Fair Market Rent is –0.71.

Access to Credit

Access to credit is an important component of financial well-being. The LMI Survey asks respondents whether access to credit for their LMI clients is better, worse, or about the same. One way to empirically validate the LMI Credit Access Index is to compare it to the degree of

credit tightening (or loosening) by commercial banks, which can be determined by the Federal Reserve's Senior Loan Officer Opinion Survey on Bank Lending Practices (Senior Loan Officers Survey). The Federal Reserve surveys 80 large domestic banks and 24 U.S. branches and agencies of foreign banks to provide "qualitative and limited quantitative information on credit availability and demand, as well as on evolving developments and lending practices in the U.S. loan markets."[13]

One of the questions asked in the Senior Loan Officers Survey is the degree to which bankers are tightening lending standards. In 2008–09, during the financial crisis, close to 100 percent of bankers reported tightening lending standards, especially on subprime loans. Figure 13 shows the LMI Credit Access Index paired with the Senior Loan Officers Survey result for banks tightening standards on mortgage loans. As banks tighten lending standards, the access to credit index should decline. Figure 13 provides evidence of this divergence. The correlation coefficient is –0.82.

Another way to measure access to credit is interest rates. As interest rates move higher, access to credit becomes more limited because some loans become unaffordable. Figure 14 shows average interest rates for auto loans ($9,000 loan at 60 months), personal unsecured loans ($1,000), and 30-year fixed rate mortgages ($175,000 loan amount). The chart reveals that the LMI Credit Access Index is negatively correlated with interest rates. Specifically, as interest rates have declined over the last decade, access to credit has improved. The correlation coefficients for the LMI Credit Access Index paired with these interest rates are -0.93 for auto loans, -0.71 for unsecured personal loans, and -0.87 for mortgage loans.

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[13]See https://www.federalreserve.gov/data/sloos/about.htm.

Financial Conditions and the Demand for Services

Two of the questions in the LMI Survey are designed to uncover broad, general assessments of economic conditions in LMI communities. One asks if the overall economic and financial well-being of LMI people has gotten better, become worse, or stayed the same. The other asks about the demand for services provided by the respondents. Higher demand for services is expected to be associated with worsening economic conditions in LMI communities, and thus the LMI Services Needs Index rises as the demand for services falls.

To empirically examine the validity of these indexes, we compared them to the Conference Board's Consumer Confidence Indexes®. The Consumer Confidence Index is available by income group, and we can thus directly compare our indexes to confidence for the LMI. We first benchmark the LMI indexes to first quarter 2011 = 100. With the fixed benchmark, opinions on economic conditions are then all relative to the value in the first quarter of 2011. We then aggregate the Consumer Confidence Indexes to quarters (average over three months) and rebenchmark them to the first quarter of 2011.

Figure 15 compares the LMI Financial Condition Index to the Consumer Confidence Indexes for those with incomes below $15,000, incomes between $15,000 and $25,000, and incomes between $25,000 and $35,000. The indexes all trend upward and generally move together.

The LMI Financial Condition Index surged upward in 2012 and 2013 relative to the Consumer Confidence Indexes. We believe the primary explanation for this movement in the index is conditions in the energy sector. The Tenth Federal Reserve District economy has a heavy energy presence. Oil prices, and to a lesser extent natural gas prices, were historically high during this period, enriching the local economies and increasing employment and incomes,

which eventually filtered down to local services. In 2014, energy prices fell rather dramatically, and the LMI Financial Condition Index retreated in tandem.

Forecasts

Another aspect of the survey that can be validated is the quality of the period ahead forecast associated with each question. We evaluate this forecast by regressing the quarter-over-quarter LMI indexes by the forecasts made in the previous quarter. Results show that the regression coefficients for job availability, access to credit, and financial condition are not statistically different from 1 (Table 4). The closer the coefficient is to 1, the better is the forecast. Coefficients for the affordable housing and demand for services indexes are statistically different from 1. Specifically, both values are below 1, suggesting that survey respondents are overly optimistic about affordable housing and demand for services. For all indexes the parameter estimates are statistically different from 0. The single regressor explained 63-73 percent of the total variation in the quarter-over-quarter data from job availability, access to credit, and financial condition. For affordable housing and demand for services, the adjusted R^2s were much lower.

6.   Conclusion

A common problem with surveys is reaching the hard to reach. The Kansas City Fed's LMI Survey, if distributed to low- and moderate-income people, would suffer from this problem. For our purposes, the ideal survey respondent is hard to reach in a couple of ways. First low-income people are generally harder to reach than are higher-income people. Secondly, even if a reasonable number of low-income people can be reached, it would be difficult to reach people

who have the necessary information and experience to answer the questions in our survey accurately.

In conducting our survey, we need to balance twin aims of representativeness and cost-effectiveness. For us, the largest cost associated with reaching hard-to-reach respondents is time. Our report is released within two months of the survey period. The short timeframe is necessary if we are to provide timely information to Fed management, policymakers, community organizations, and the public. If the survey were to question LMI households directly, headline results could take months to release.

In this paper we describe our target population and why they are hard to reach. We then explain how we use a database of organizations that serve the LMI population as a proxy for the LMI population. Our analysis then explores potential problems with using a nonrandom sample and concludes that the use of a nonrandom sample is not a significant problem for our survey. Finally, we address the empirical validity of the survey and conclude that the survey does a good job of describing economic conditions in LMI communities.

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TABLES

Table 1: t-tests for Difference in Means, Standard and Parallel Survey

Index	Standard Sample Mean (Std. Error)	Parallel Sample Mean (Std. Error)	p-value
Financial Condition (quarter)	65.9 (4.3)	72.7 (6.4)	0.270
Financial Condition (year)	64.7 (4.8)	70.5 (7.5)	0.324
Financial Condition (Expectations)	76.5 (4.8)	73.9 (4.8)	0.381
Demand for Services (quarter)	56.5 (4.6)	45.5 (5.6)	0.126
Demand for Services (year)	50.6 (4.7)	22.7 (5.4)	< 0.001
Demand for Services (expectations)	50.6 (4.2)	47.7 (5.4)	0.365
Job Availability (quarter)	108.2 (4.8)	104.5 (4.8)	0.344
Job Availability (year)	118.8 (4.9)	111.4 (6.2)	0.255
Job Availability (expectations)	116.5 (4.6)	106.8 (5.7)	0.169
Affordable Housing Availability (quarter)	71.2 (4.8)	61.4 (5.4)	0.159
Affordable Housing Availability (year)	65.9 (5.0)	60.2 (6.0)	0.307
Affordable Housing Availability (expectations)	74.7 (5.1)	69.3 (5.6)	0.310
Access to Credit (quarter)	83.5 (3.6)	84.1 (5.1)	0.397
Access to Credit (year)	84.1 (3.9)	92.0 (5.4)	0.196
Access to Credit (expectations)	90.0 (3.9)	92.0 (4.9)	0.378
Funding (quarter)	83.5 (5.1)	117.0 (7.4)	< 0.001
Funding (year)	84.1 (5.6)	122.7 (8.3)	< 0.001
Funding (expectations)	85.3 (4.9)	118.2 (7.5)	< 0.001
Capacity (quarter)	98.8 (5.1)	122.7 (7.2)	0.010
Capacity (year)	102.9 (5.5)	130.7 (7.7)	0.005
Capacity (expectations)	107.1 (5.4)	126.1 (7.5)	0.046
Bootstrap; 10,000 replications			

Table 2: Regression Results, Scatter Plot, Standard and Parallel Surveys

Index	Parameter (Std. Err.)	Pr > |t| (H0: β = 0)	Pr > |t| (H0: β = 1)
Quarter-over-Quarter	0.995 (0.108)	0.003	0.484
Year-over-Year	0.755 (0.143)	0.013	0.080
Expectations	0.805 (0.162)	0.016	0.149

Table 3: Comparison Statistics, Job Availability Index (year-over-year)

	K-S Statistic (p-value)	Correlation Coefficient
Boston	0.375 (0.211)	0.712
Dallas	0.579 (0.003)	0.941
Philadelphia	0.368 (0.152)	0.690

Table 4: Regression Results, Quality of Forecasts

Index	Intercept	Forecast	Adjusted R^2
Job Availability	−20.15 (16.03)	1.098** (0.157)	0.65
Affordable Housing	36.40* (15.60)	0.496** (0.176	0.21
Access to Credit	−19.82 (10.92)	1.14** (0.137)	0.72
Demand for Services	18.10* (7.613)	0.599** (0.141)	0.39
Financial Conditions	−13.31 (11.31)	1.021** (0.151)	0.63
**,* indicates significance at 0.01 percent and 0.05 percent, respectively			

FIGURES

Figure 1: LMI Job Availability Index
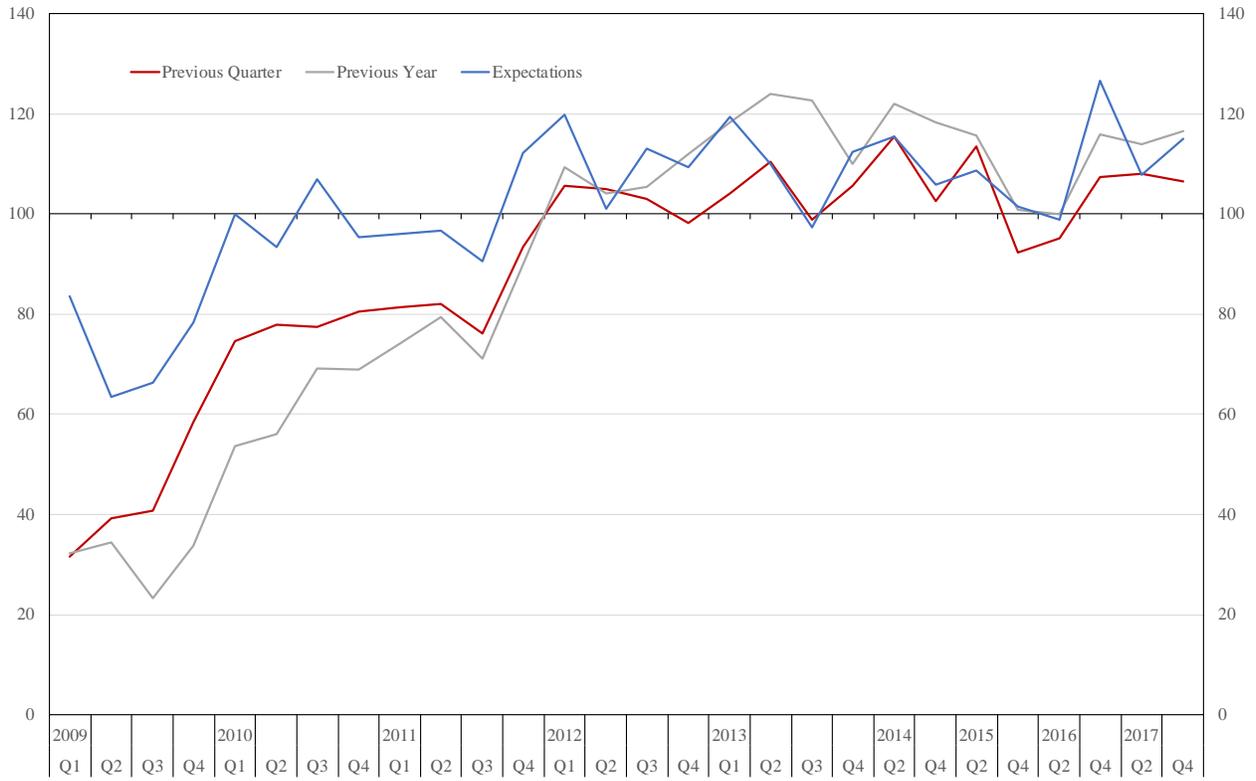
Source: Federal Reserve Bank of Kansas City LMI Survey

Figure 2: LMI Diffusion Indexes

Source: Federal Reserve Bank of Kansas City LMI Survey

Figure 3: Word Cloud, Comments on Job Availability
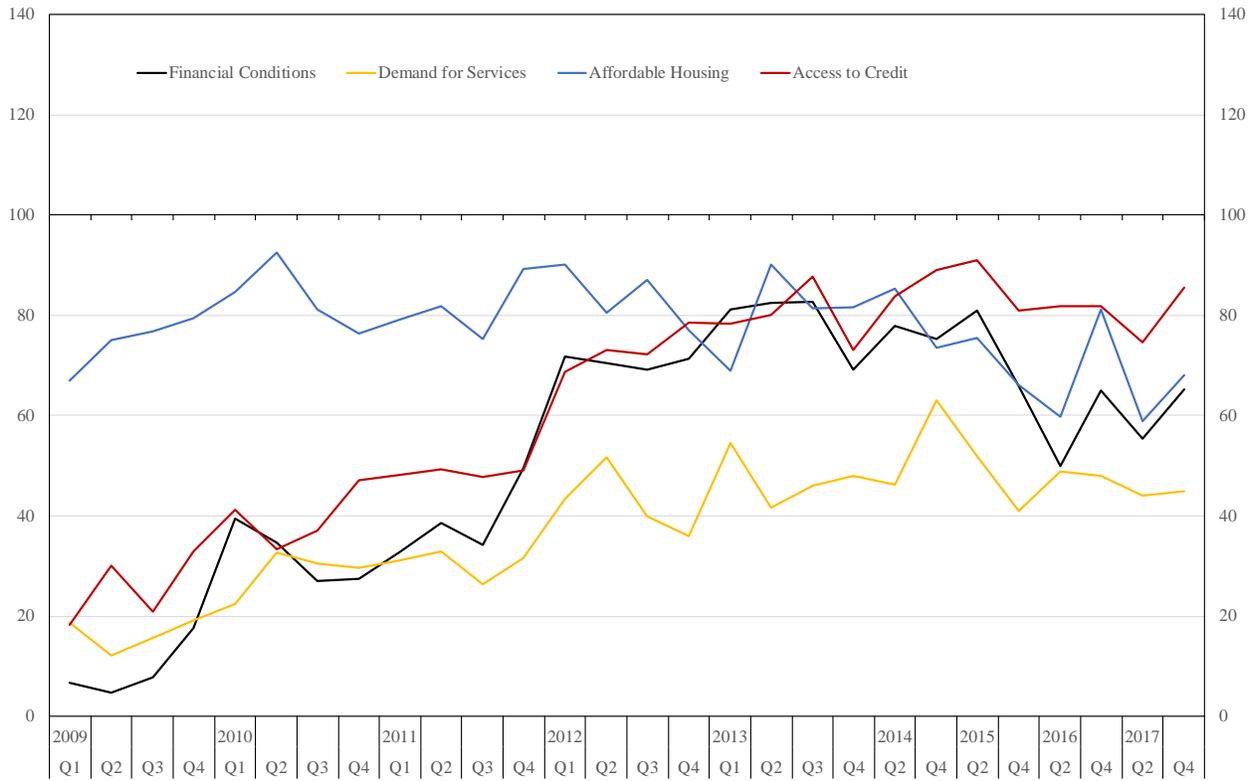
Source: Federal Reserve Bank of Kansas City LMI Survey

Figure 4: Balance of Opinion, Standard and Parallel Surveys, with Confidence Intervals
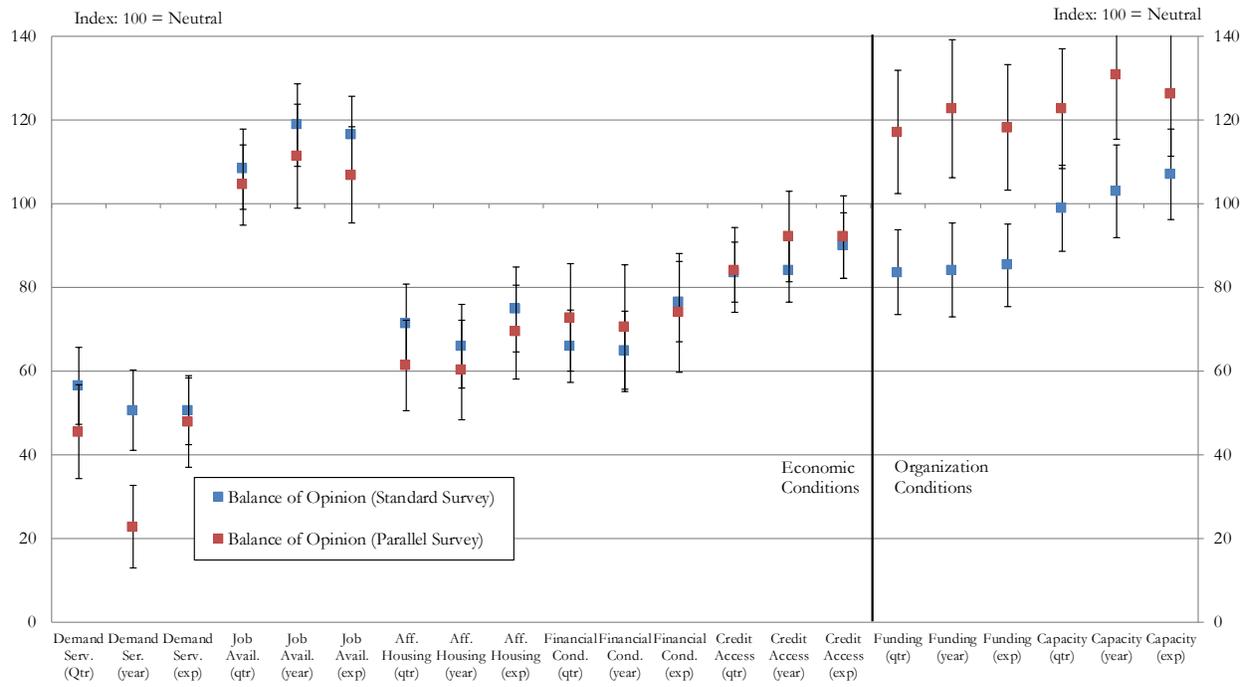
Source: Federal Reserve Bank of Kansas City LMI Survey

Figure 5: Diffusion Index, Funding, quarter-over-quarter, Frequent and Infrequent Responders
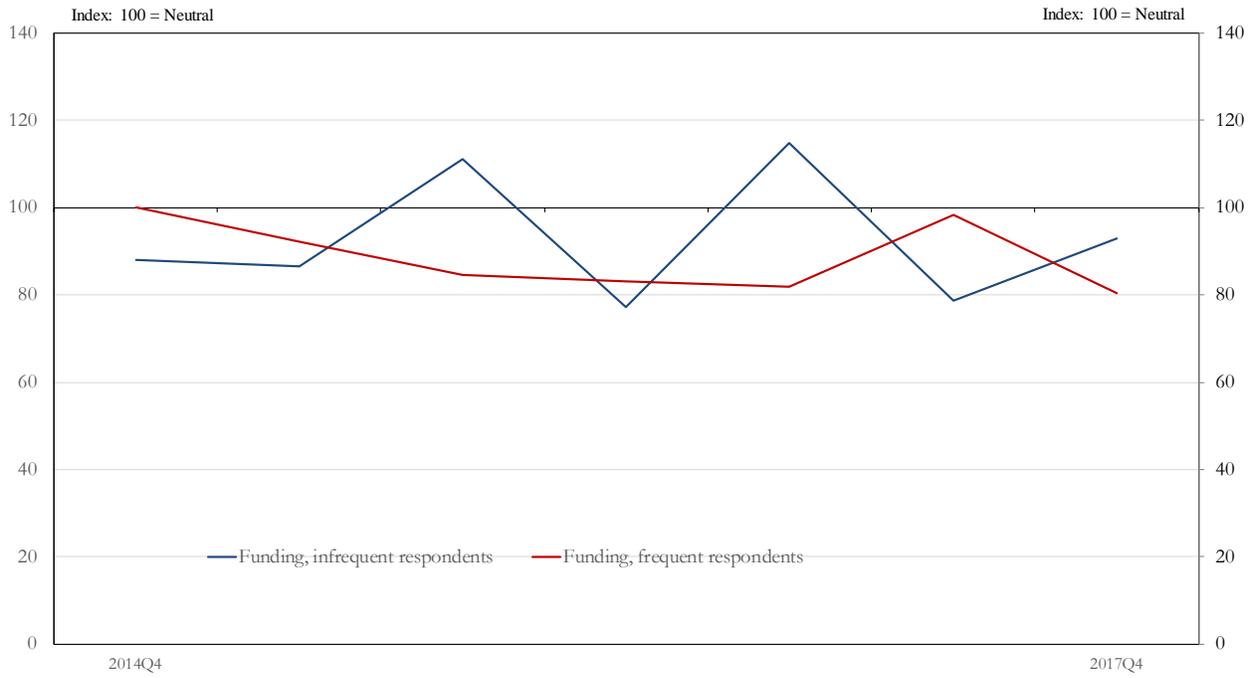
Source: Federal Reserve Bank of Kansas City LMI Survey

Figure 6: Regression Lines, Standard and Parallel Surveys
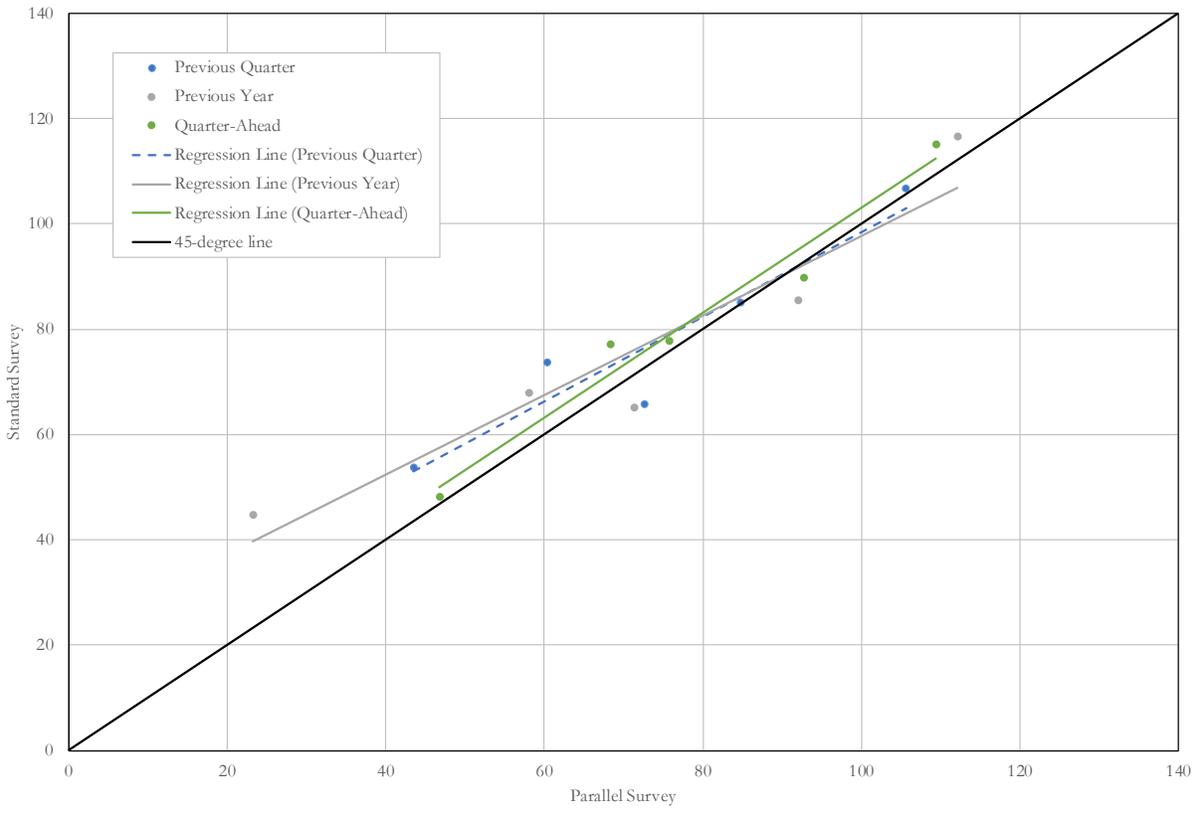
Source: Federal Reserve Bank of Kansas City LMI Survey

Figure 7: Diffusion Indexes Across Federal Reserve Banks, Job Availability, Year-over-Year
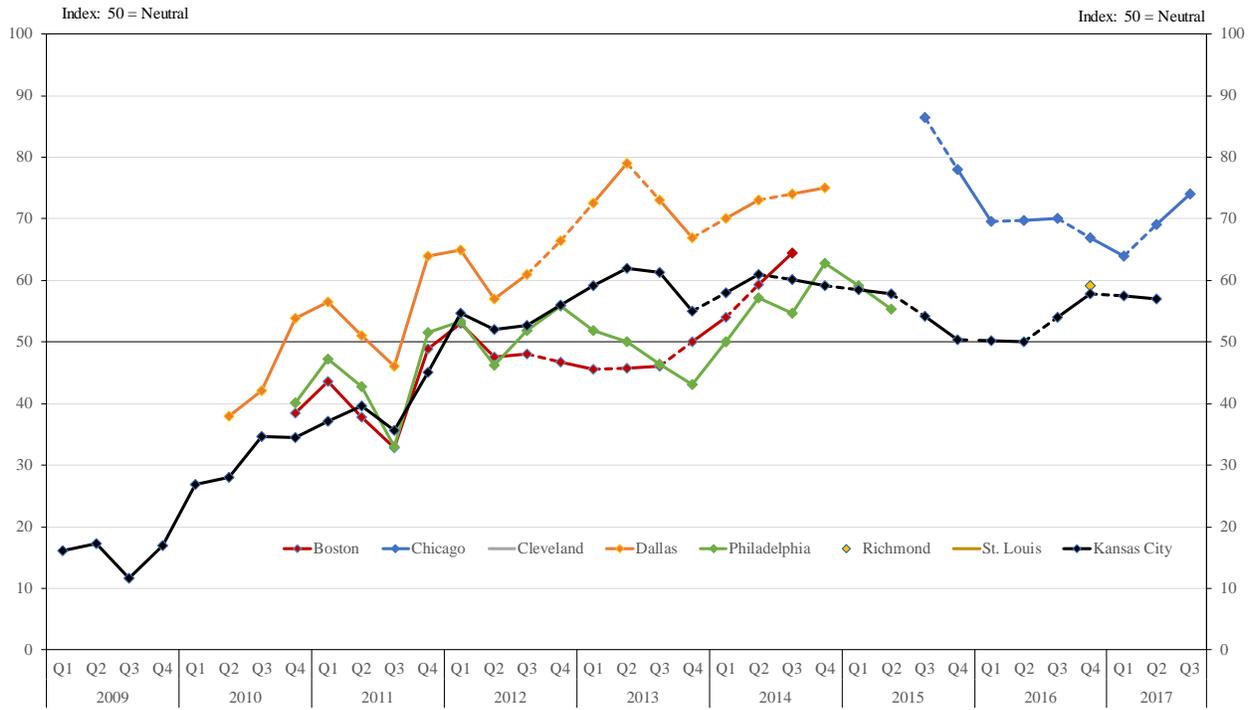
Federal Reserve Banks

Figure 8: LMI Job Availability Index and Employment Growth in Accommodations & Food Services and Retail Occupations

Sources: Federal Reserve Bank of Kansas City LMI Survey; Occupational Employment Statistics, U.S. Bureau of Labor Statistics /HAVER Analytics

Figure 9: LMI Job Availability and Tenth Federal Reserve District Employment in Leisure & Hospitality, Retail, and Services Industries
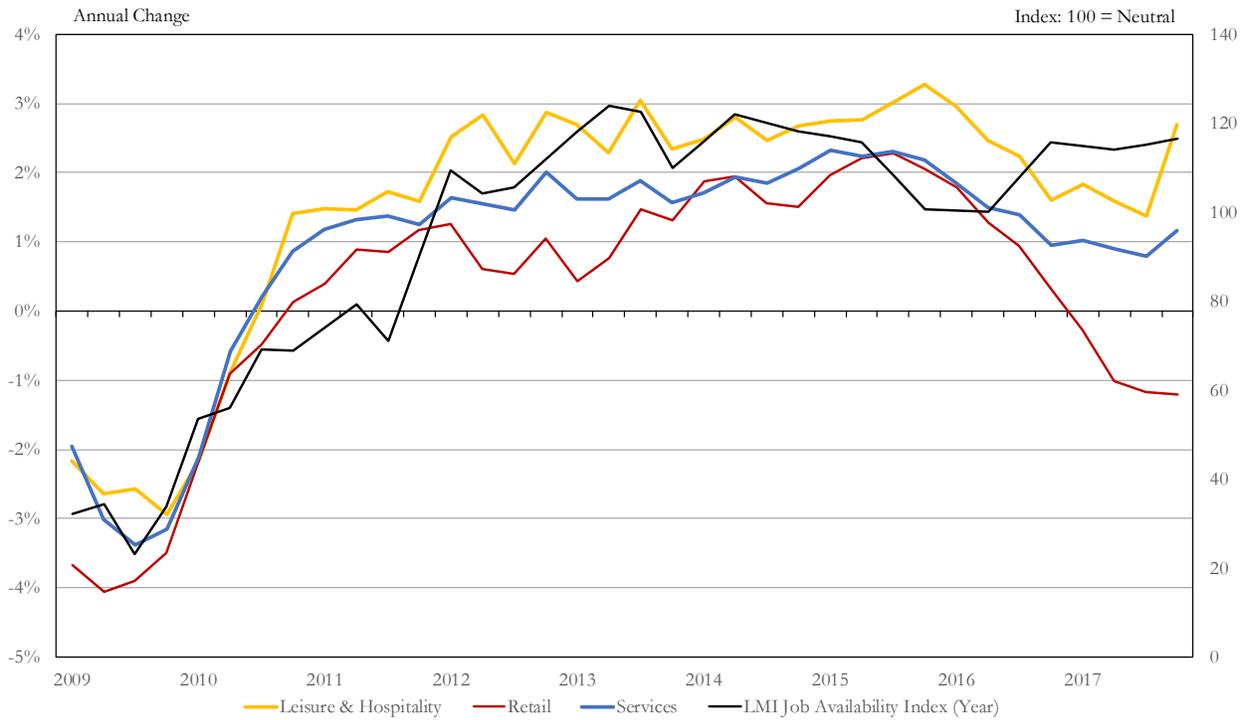
Sources: Federal Reserve Bank of Kansas City LMI Survey; Establishment Survey, U.S. Bureau of Labor Statistics /HAVER Analytics

Figure 10: LMI Job Availability Index and Employment Growth by Educational Attainment
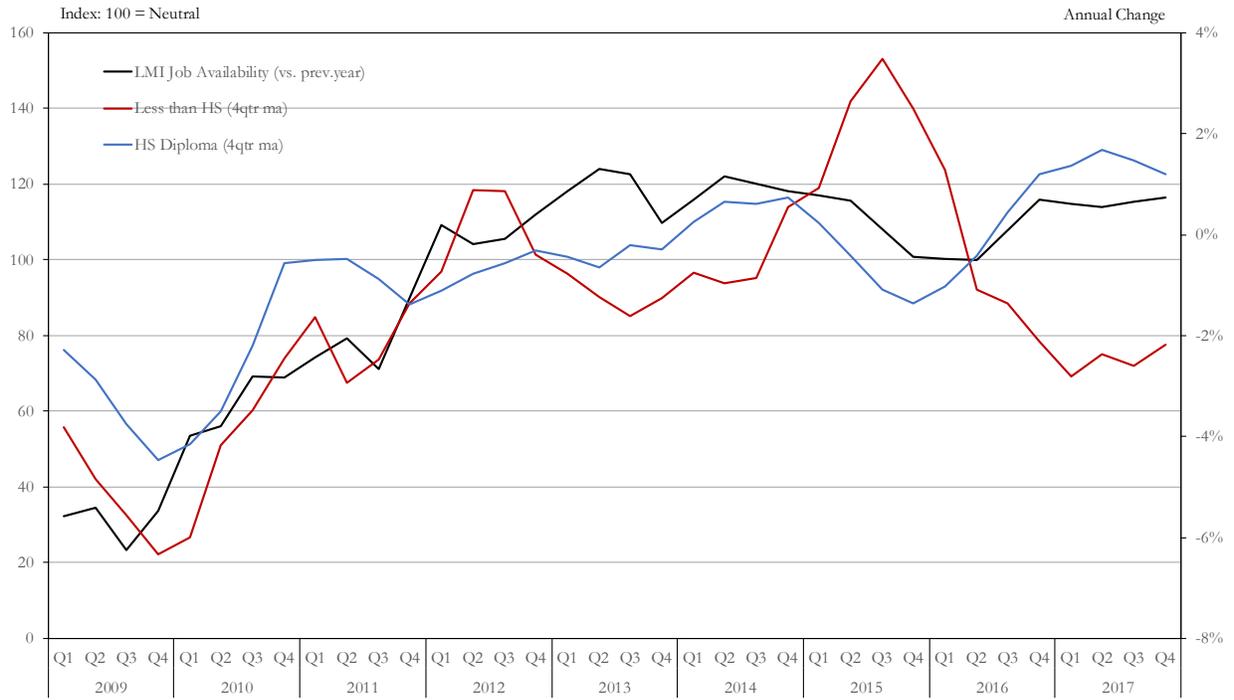
Sources: Federal Reserve Bank of Kansas City LMI Survey; U.S. Bureau of Labor Statistics

Figure 11: LMI Job Availability Index and Employment Growth by Race and Ethnicity
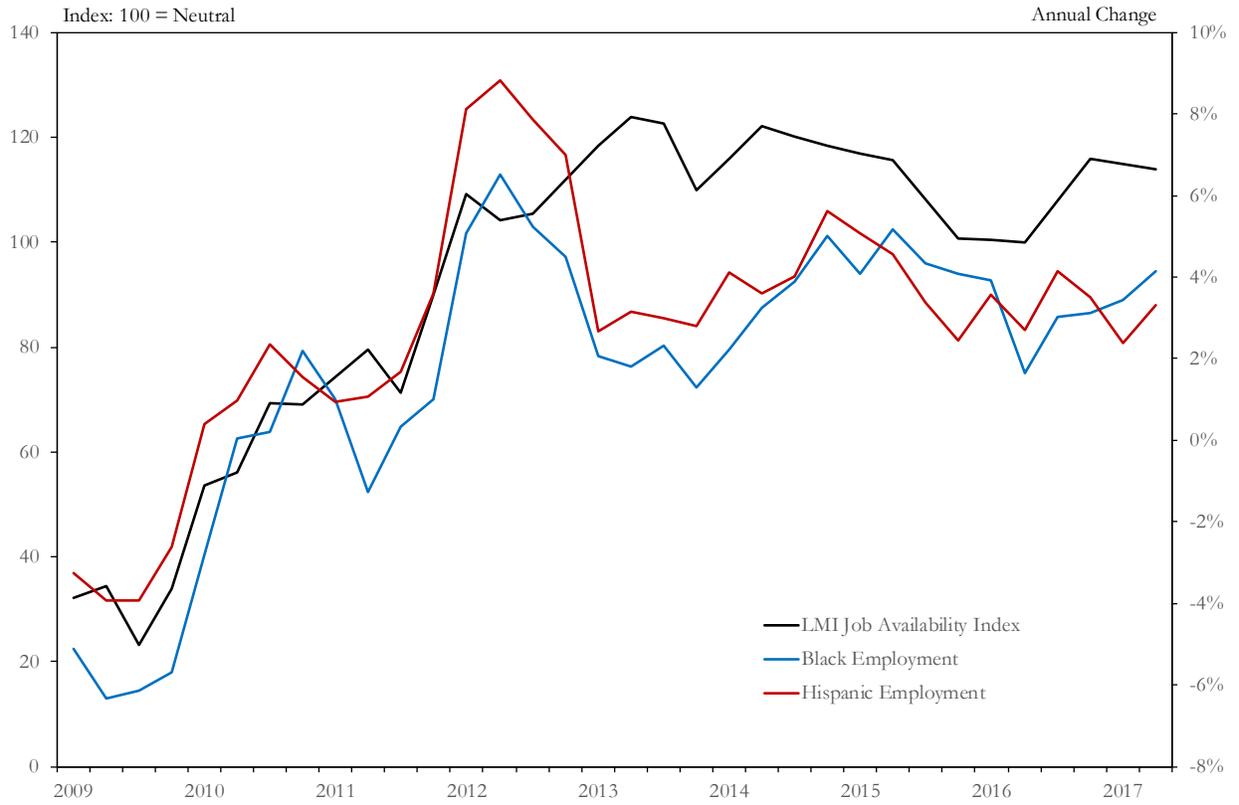
Sources: Federal Reserve Bank of Kansas City LMI Survey and U.S. Bureau of Labor Statistics

Figure 12: LMI Housing Affordability Index and Fair Market Rents
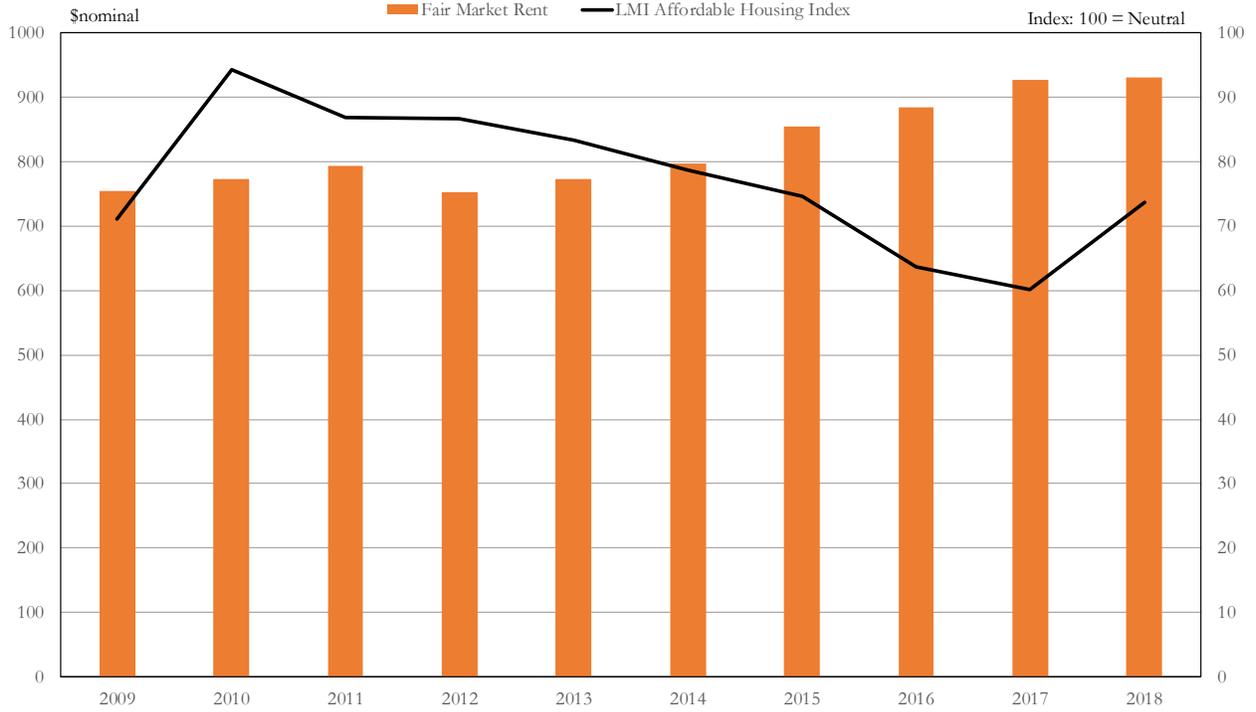
Sources: Federal Reserve Bank of Kansas City LMI Survey and U.S. Department of Housing and Urban Development

Figure 13: LMI Access to Credit Index and the Senior Loan Officers Survey
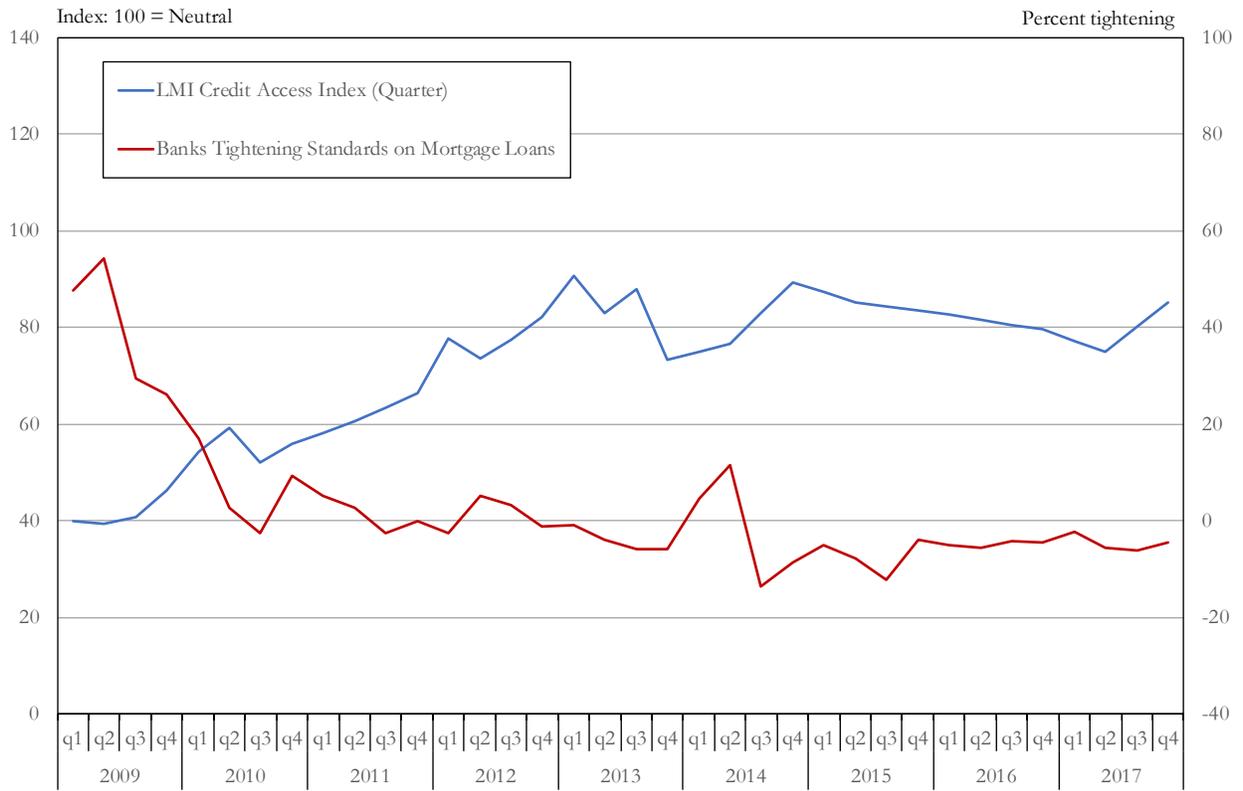
Sources: Federal Reserve Bank of Kansas City LMI Survey and Federal Reserve Board Senior Loan Officers Opinion Survey /HAVER Analytics

Figure 14: LMI Access to Credit Index and Selected Interest Rates
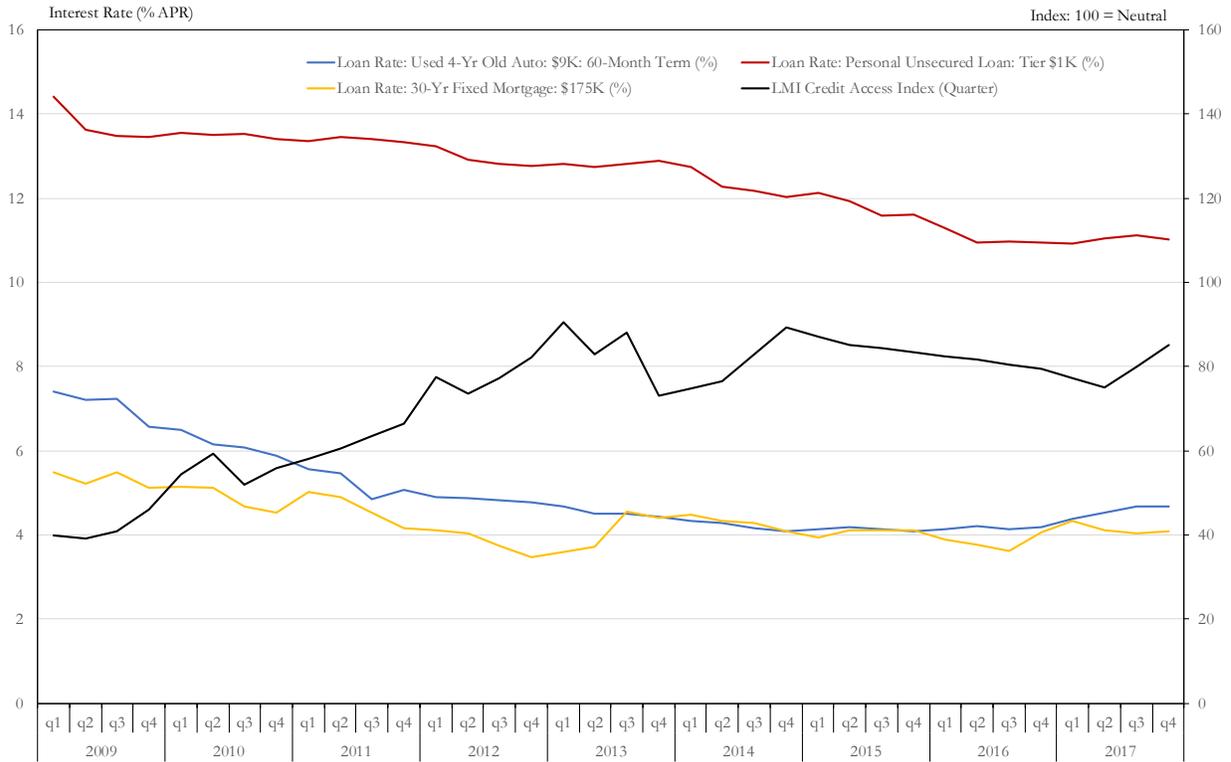
Sources: Federal Reserve Bank of Kansas City LMI Survey; Federal Reserve Board /HAVER
Analytics

Figure 15: LMI Financial Condition Index and The Conference Board Consumer Confidence
Index

Index: March 2011 = 100
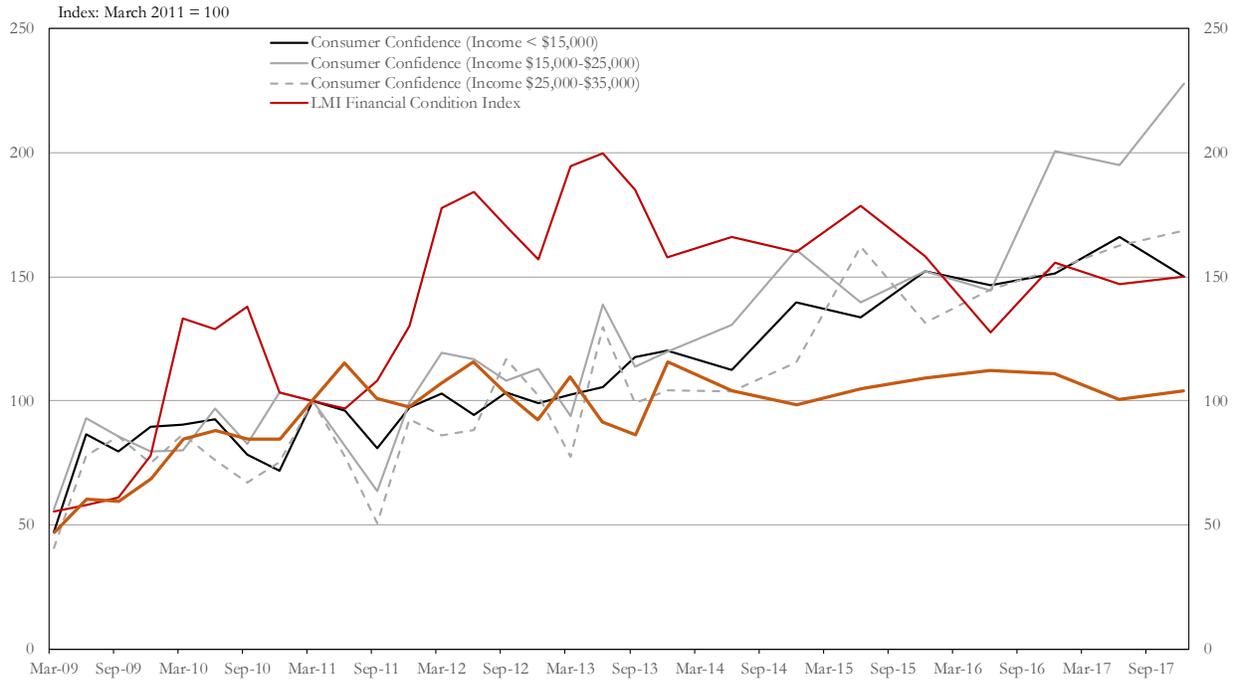
Sources: Federal Reserve Bank of Kansas City LMI Survey; The Conference Board /HAVER
Analytics