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Immigration and Prices

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Abstract
This paper exploits the unexpected arrival of 200,000 FSU immigrants to Israel during 1990 to empirically examine the effect of a change in demand on prices. The main finding is that immigration had a moderating effect on prices during 1990. Controlling for the selection of immigrants into cities and for population growth, a 1 percentage point increase in the share of immigrants in a city decreases prices by about 1.4-1.8 percent. Even when the increase in population is accounted for, the overall effect of immigration on prices remains negative. This downward effect on prices is stronger in products where demand increases are larger. The negative immigration effect can be explained by the new immigrants searching more intensively for lower prices than the native population. In support of this interpretation, it is shown that the relationship between price dispersion across stores and the share of immigrants has an inverse-U shape as implied by Stahl's (1989) model of search.

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1 Introduction

In the standard perfectly competitive model when demand increases price should either remain unchanged or increase. Yet, a growing body of evidence indicates that, contrary to this prediction, retail prices fall in periods of high demand (Warner and Barsky, 1995; MacDonald, 2000; Chevalier et al., 2003). In this paper I examine the price effects of the large increase in demand resulting from the massive and unexpected arrival of former Soviet Union (FSU) immigrants to Israel in 1990. The results in this paper are in line with the recent empirical evidence, but for different reasons.

Since the end of 1989, and until 1995, a large inflow of immigrants from the former Soviet Union arrived in Israel, with monthly immigration flows increasing exponentially during 1990 (see Figure 3). Immigrants are not only workers but also consumers of goods and services, and this raises the question of whether immigration has an effect on prices. In general, one would not expect this effect to be large because immigration flows are usually predictable and small relative to the size of the native population. In the Israeli experience, however, the large size of the FSU immigration – reaching 4 percent of the population at the end of 1990 – and its unexpected nature combined in such a way as to leave measurable traces in the price data.

I use monthly, store-level price data for 478 products sold by 1300 stores located in 52 cities in Israel during 1990 to relate price changes in cities to changes in their population size and composition – their share of FSU immigrants. The share of FSU immigrants was essentially zero in all cities in October 1989 – before the start of the immigration wave – but by December 31, 1990 it ranged between 0 and 15 percent across cities (see column (6), Table 1). This significant variation in the spatial distribution of FSU immigrants is used to identify the effect of immigration on prices.[1] Essentially, I regress prices in a city on the share of immigrants and on population in the city, accounting for product, city, and month effects.

[1] A before-after comparison is not feasible because dissagregated price data are not available before January 1990. Comparing prices within 1990 is problematic, not only because immigration was already in full swing, but mainly because there are no monthly immigration data by city to match the monthly price data.

The main empirical finding is that immigration had a moderating effect on prices during 1990. Controlling for the selection of immigrants into cities and for population growth, a 1 percentage point increase in the share of immigrants in a city decreases prices by about 1.4-1.8 percent. Even when the increase in population is accounted for, the overall effect of immigration on prices remains negative although its magnitude is reduced (in absolute value). The negative immigration effect holds for almost all product groups, and is stronger in products where immigrants represent a larger share of the expenditure. Thus, the downward effect on prices is stronger in products where demand increases are larger. It is also stronger during the second half of the year when 2/3 of the immigrants arrived. The estimates imply an upper bound to the gain in consumer surplus of $1,290 - $1,650 per household in 1990.

Although these findings agree with the countercyclical behavior of retail prices observed in recent studies, the underlying model explaining these results is different. By focusing on the short-run – the year 1990 only – I rule out supply-based explanations of the negative immigration effect. The explanations have to be demand-driven. But demand-driven models generating countercyclical prices, such as Rotemberg and Saloner (1986) and Warner and Barsky (1995), are appropriate for analyzing price fluctuations due to temporary shocks or to cycles in demand such as weekends and holidays rather than to permanent shifts in demand.

Models relying on new immigrants having a higher price elasticity than natives, such as Bils (1989), would imply predictions consistent with a negative immigration effect. These models, however, are based on consumers having full information on prices. When consumers do not have full information about prices and acquiring information about them is costly, stores develop some market power and are consequently less motivated to reduce their prices. Indeed, Diamond (1971) showed that prices will converge to the monopoly price. It is the presence of a mass of consumers with negligible search costs that can motivate shoppers to lower their prices. This is the role played by the FSU immigration. Thus, the negative effect of the immigration share can be explained by the new immigrants searching more intensively for lower prices than the native population.

The available data indicate that immigrants spent significantly more time shopping than non-immigrants, and that they did not participate in the labor force immediately after their arrival in the country, suggesting that their alternative cost of search was lower than that of the native population. Furthermore, price dispersion across stores first raises with the share of immigrants and then declines. This non-trivial result is predicted by Stahl's (1989) model of consumer search but is absent from explanations based on immigrants having higher price elasticities than natives. Thus, the results in this paper are consistent with an increase in demand accompanied by an increase in the amount of search conducted in the market.

Under this interpretation the results in this paper also contribute to the empirical literature on the effect of search on the price level. Sorensen (2000) shows that prices of drugs that are repeatedly purchased, and therefore more likely to benefit from search, exhibit significant reductions in price-cost margins relative to occasionally purchased drugs. Similarly, the Internet reduces search costs by facilitating cheap and fast price comparisons. This should result in increased search activity leading to lower prices. Brown and Goolsbee (2002) find that "...the rise of Internet use from 1995 to 1997 reduced term life [insurance] prices by 8-15 percent".[2] In this context, the present paper could be read as proxying the amount of search in the market by the share of immigrants instead of by the share of Internet users.

The paper is organized as follows: Section 2 presents the price and immigration data and some preliminary, non-parametric evidence on the price-immigration relationship. Section 3 develops an econometric model whose results are described in Section 4. Finally, in Section 5 possible explanations of the estimated effects are discussed and evidence in support of a search-based interpretation is presented. Conclusions close the paper.

[2] Yet, the empirical evidence on the competitive effects of the Internet is somewhat mixed. Brynjolfsson and Smith (2000) also report lower prices in the Internet for books and compact disks during 1998-99. But Clay, Krishnan and Wolff (2002) find that prices and price dispersion in 32 online bookstores did not fall during 1999-2000, as the use of the Internet increased.

2 Description of the Data

2.1 A Short-run Analysis

The ideal experiment would be to compare prices in 1990 to prices in 1989, before the FSU immigration started. Regretfully, this is not possible because prices for the period before January 1990 are not available at the CBS in a way amenable to academic research. I focus therefore on 1990, the first year of the FSU immigration. For several reasons, I believe this to be the most appropriate time frame for examining the impact of an increase in demand on prices.

First, supply can be taken to be approximately fixed through the year. There was a lot of uncertainty, especially during 1990, regarding the future flows of FSU immigrants. Suppliers waited before they committed resources to open new stores or to expand production beyond what was planned.[3] Over the years, however, stores changed their product composition, and new, dedicated, stores were opened catering to immigrants's tastes. Although these supply changes could also be attributed to the immigration, for the purposes of estimating the basic relationship between demand and prices it is better to ignore these long-run effects. Focusing on 1990 achieves this.

Second, by focusing on 1990 we can safely ignore changes in natives' demand as a result of changes in income or other fiscal measures prompted by the FSU immigration.[4] This means that the estimated immigration effect, after controlling for market size, is more likely to reflect the price effect of the change in the immigrant population and not an effect through changes in natives' local demand.

Finally, the 1990 wave of immigrants was quite ignorant about the market economy

[3]The only source of data on the number of stores by city is from the Value Added Tax Authority. These data are problematic because, among other things, they do not capture the opening or closing of branches of multi-branch firms since the VAT is paid by the central office. Under this caveat, the growth rate in the number of firms paying VAT in eight major cities in Israel between 1989 and 1990 was not significantly different from that between 1990 and 1991. Data for years before 1988 are not available. The cities are Beer Sheva, Eilat, Givataym, Haifa, Holon, Jerusalem, Ramat Hasharon and Tel-Aviv.

[4]Natives' wages were apparently not much affected by the FSU immigration (Friedberg, 2001). Cohen-Goldner and Paserman (2003) show that natives' employment was not affected either, but they find a small negative effect on their wages in the short run. In 1990, no new taxes were imposed to finance the absorption of immigrants.

in general and that of Israel in particular. Subsequent waves of FSU immigrants were more informed about the Israeli economy and possibly more "westernized". This suggests that immigrants' consumption behavior may have differed across cohorts in important ways that cannot easily be controlled by cohort dummies.[5] Focusing on 1990, isolates the changes in demand caused by a relatively homogeneous group of new consumers.

2.2 The Price Data

The price data consist of monthly price quotations obtained from retail stores by the Central Bureau of Statistics (CBS). Once a month, the CBS samples prices on a variety of goods from a sample of stores, and uses them to compute the monthly Consumer Price Index.[6] The CPI includes prices of about 1100 products but because of limited resources we decided to use only 478 items. These 478 products were selected in a semi random way: housing and all fruit and vegetable products–for which quality differences are difficult to measure– were excluded but a few products that were thought to be in high demand by FSU immigrants such as pork products and alcoholic beverages were included.

The empirical analysis is based on monthly price quotations for the year 1990 from 1300 retail stores located in 52 cities in Israel. The cities and the number of sampled stores in each of them appear in Table 1, columns (1) and (2). In the large cities (Tel-Aviv, Jerusalem, Haifa) over a hundred stores are visited and, as shown in column (3), most products are sampled (e.g., Tel Aviv has prices for 467 of the 478 products), but in the small towns (e.g., Sederot) only a few stores are visited and just a fraction of the products are sampled (e.g., less than 10 percent of the products in Sederot). As a result, the number of total price observations by city in column (4) ranges from less than 100 (in Sederot) to almost 15,000 (in Tel Aviv).

[5] Weiss et al. (2003) show that over time immigrants' income catches up with that of natives so that, also in terms of income, the share of immigrants in latter years is not composed of homogeneous immigrants.

[6] Importantly, the price data are not "scanner" data. The prices are therefore "asking" prices. For many products, asking and actual transaction prices are identical. The price data used by Lach and Tsiddon (1992, 1996) and Lach (2002) came from the same source–the CPI raw data collected by the CBS–but were limited to a restricted set of products, and to different time periods.

The number of price quotations (i.e., of stores) per product also varies considerably. In general, the sample size depends on the popularity of the product. For example, "jeans" were sampled in 56 stores but "metal chairs" were sampled in only 3 stores.[7] In Figure 1, the height of the bar at a particular value in the horizontal axis is the number of products having that particular sample size. As expected, the distribution of the number of price quotations is skewed to the right with just a few products having large sample sizes. Half the products have sample sizes of 15 stores or less, and only 9 percent of all products–45 products–have samples with 30 or mores stores.

On average, 11.4 products are sampled in each monthly visit to a store. The distribution of sampled products by stores is also skewed to the right with half the stores having less than 7 products sampled, while 5 percent of the stores have over 37 price quotations for different products in each month. Figure 2 plots the distribution of the monthly number of products sampled in each store.[8]

Each product file has a city and store identifier, a nominal price quotation observed during the month, information on the manufacturer, brand, size, weight, and other relevant characteristics of the product. Thus, a "single" product comprises different variations of the product in terms of the manufacturer's identity, brand, size, weight, packaging, etc. For example, hummus, a popular food product, has up to eleven variations of the product. This information was coded both numerically and in Hebrew. We checked each file manually in order to quantify the information appearing in Hebrew and to check for consistency between both sources of information. This labor-intensive process is the main reason for restricting the analysis to about half the number of items in the CPI. We realized, however, that any attempt to "dummify" this information and use it to control for differences in price levels would be futile: different set of characteristics are relevant (with varying importance) for different products and each product has too many variations. Thus, a regression analysis of price *levels* which does not control for

[7]This "number of stores", and the ones used in Figure 1, are an average of the monthly number of stores sampled for each product which may vary slightly from month to month.

[8]This "number of products", and the ones used in Figure 2, are an average of the monthly number of products sampled in each store which may vary slightly from month to month.

product-specific characteristics, is probably not the best approach if one suspects that these omitted product characteristics may be correlated with the share of immigrants, the regressor of interest.

The variation in a product's characteristics is usually across stores and not within stores (i.e., over time). This is so because the CBS is interested in knowing the price *change* of the *same* product for the computation of the CPI. Thus, we can be quite sure that within a store, the price quotations from month to month refer exactly to the same product.[9] This suggests, of course, that in analyzing the determinants of monthly price *changes* we are accounting for all those product characteristics which remain constant over time, and even for store and city features that do not vary from month to month.

The number of reporting stores changes over time because new stores are added to the sample while others drop out, and also because stores that are out of stock when visited by the CPI data collector are assigned a missing value for that month. Table 2 shows the distribution of stores' duration in the sample during 1990. Duration is computed for each store–product combination in the sample.[10] Durations are short: half the stores appear during less than five months and no store-product combination has price quotations for more than 9 months.[11]

2.3 The Immigration Data

The first FSU immigrants started to arrive in Israel during the last months of 1989 as a direct consequence of the political developments in the Soviet Union. Even though the

[9]For example, in store 1 the CBS always tries to obtain a price quote for a bottle of brand A beer and in store 2 a price quote for a brand B beer.

[10]There are 16,663 store-product observations. In a store where two products are sampled one product may be sampled from January to May and the other from July to December. This store generates two durations of 5 and 6 months, even though the store is in the sample during 11 months.

[11]The reason for the short durations is a technical one: the CBS moved gradually from using large mainframes to using PCs during the year 1990. As a result, not all the data in the mainframe was transferred to the PC. This is particularly true for the first half of 1990, the initial phase of the transition. In the second half of 1990, when the transition was almost complete, over 75 percent of the durations in the stores appearing in the sample for the first time in July 1990 are at its maximum (6 months). As long as the reasons for the missing data are random this should not affect our estimation. In any case, as mentioned in Section 4, using data only for the second half of 1990 gives even stronger results.

process leading to the collapse of the Soviet Union in 1991 was set in motion years before, the massive immigration caught Israel completely unaware.[12] The monthly inflow of FSU immigrants grew from about 1500 in October 1989 to about 35,000 in December 1990. Figure 3 shows the monthly flow of immigrants during 1989-1995. During the period October 1989-December 1990, about 200,000 FSU immigrants arrived in Israel and their share in the total population reached an astounding 4 percent by the end of 1990. The immigration process continued during the first half of the 1990s but at a decreasing rate. During 1991, 145,000 immigrants arrived in Israel but during 1992-95, the yearly inflow was around 65,000.

Immigrants did not settle uniformly over the country. As seen in column (6) of Table 1, the variation in the proportion of immigrants across cities (at the end of December 1990) is quite large. There are many locations (e.g., Arab towns) where there are no immigrants at all, while in others cities (e.g., Karmiel, Nazareth Illit, Qiriat Yam), their share is over 10 percent at the end of 1990. The simple average of immigration shares across cities is 4.9 percent and the standard deviation is 3.2 percentage points.[13] This variation will be used to identify the effect of immigration on prices.

An important limitation of the immigration and population data is that we do not have city-level data for every month of the year. The total population figures by city are available only for 31 December 1989 and 1990, while data on FSU immigrants are available only for 31 December 1990. We will return to this issue in Section 4.

2.4 Preliminary Data Analysis

The monthly average price change of a product j in store i in city c is computed as the difference in log price between the last (t_{1ij}) and first (t_{0ij}) months the store-product is observed in the sample divided by the duration in the sample, $\frac{\log p_{jict_{1ij}} - \log p_{jict_{0ij}}}{t_{1ij} - t_{0ij}}$. I then average all these price changes over all products and all stores in the city and this is the

[12] The *glasnost* and *perestroika* reforms were introduced in 1985-87.

[13] The unweighted average of immigrant shares across cities (4.9 percent) is higher than the weighted (national) average (3.9 percent) reflecting the large shares of immigrants in small cities.

figure appearing in the last column of Table 1.[14] The simple average of the monthly price changes is 0.9 percent but there is large variation across cities ranging from 2.1 percent in Sederot to 0.3 percent in Ashqelon, Ra'anana, Ramat Gan and Sachnin (the standard deviation across cities is 0.4 percentage point). The price change and immigration share data are plotted in Figure 4 along with the fitted value of a linear regression. The slope of the fitted line is negative but not precisely estimated (estimated slope is -0.024 with standard error 0.018).

Instead of correlating city-averages I use all the data at the store-product level to estimate the expectation of the monthly price change $\Delta \log p_{jict} = \log p_{jict} - \log p_{jict-1}$ conditional on the immigrant share S_c, $E(\Delta \log p_{jict}|S_c)$. I estimate this expectation non-parametrically using Fan's (1992) locally weighted regression smoother (Figure 5). The conditional expectation shows a clear inverse relationship with the share of immigrants for most values of S in the sample.

These results suggest that prices increase less rapidly in cities where the share of immigrants is larger. By looking at price changes we control for product, store and city effects and this should also control for the selection of immigrants into cities. However, changes in market size and differential inflation rates among products are ignored. To verify that these preliminary results are robust to the presence of other controls, and to get some quantitative assessment of the estimated relationships and their precision, we proceed to a regression-based analysis of the data.

3 Econometric Specification

The focus of this paper is on the effect of a change in the size and composition of demand on prices. Since we analyze the short-run we are implicitly holding constant all other factors affecting prices (e.g., market structure). This is captured in the following specification for the nominal price of product j sold by store i in city c during month

[14] Computing the change between the *average* price in December 1990 and the *average* price level in January 1990 would involve comparing prices from different stores since no store-product observation is in the sample for more than 9 months (see Table 2). This may introduce a composition bias in that the price averages are based on prices of brands that may differ between the two samples.

$t = 1, \ldots, 12$,

$$p_{jict} = L_{ct}^{\beta_j} e^{\delta_j S_{ct}} e^{A_{jict}} \tag{1}$$

where L_{ct} is the population size in city c in month t which serves as a proxy for demand size, S_{ct} is the share of immigrants in the city which captures the composition of demand, and A_{jict} is an unobserved term. For the moment ignore the fact that L and S are not observed on a monthly basis.

The relevant market for each product is implicitly defined as the city where the store selling the product is located.[15] Notice also that the market size and composition parameters are assumed to be product-specific. The unobserved term A_{jict} is specified as

$$A_{jict} = \mu_j + \mu_t + \mu_{jt} + \mu_i + \mu_c + u_{jict} \tag{2}$$

μ_j and μ_t are product and month dummies that capture permanent differences in price levels among different products and common time-trends in prices, respectively. The price effects of the various religious holidays are also picked up by the month dummies. The presence of the interaction term μ_{jt} allows for product-specific inflation rates (e.g., national sales of product j). μ_i captures the effect of time-invariant features of the store that bear upon prices, such as location within the city, type of store, quality of service, etc. μ_c picks up features of the city's population (income, education, etc.), city-wide amenities (presence of a shopping mall, pedestrian district, etc.) and even aspects of the market structure that are constant during the sample period. u_{jict} is a shock to price in month t.

Note that the presence of the various error components allows for a rich pattern of correlations among prices. Correlations within stores are accounted for by the store effects, while correlations in the price of the same product across stores are captured by the product effects. In addition, any correlation among products sold in the same city are accounted for by the city effects.

Equation (1) should be understood as a reduced-form equation showing the equi-

[15] But in the empirical section I show that the results are robust to alternative definitions of the market.

librium price determined by the values of L, S and A. The standard competitive model implies $\beta_j > 0$, at least in the short run. The immigration effect is given by δ_j. If immigrants behave in the same way as natives then demand composition should not matter, implying $\delta_j = 0$. On the other hand, models where new consumers have higher price elasticities and/or search more intensively for lower prices would imply $\delta_j < 0$ (see Section 5).[16]

Taking logs of equation (1) and using (2) gives

$$\log p_{jict} = \mu_j + \mu_t + \mu_{jt} + \mu_i + \mu_c + \delta_j S_{ct} + \beta_j \log L_{ct} + u_{jict} \tag{3}$$

Estimation of the parameters in the price level equation (3) is problematic for two reasons. First, product j includes many different variations of the product (brand, size, packaging, etc.). It is impractical to dummify all the variations within product j or their different characteristics. Since these characteristics may be related to the size and composition of the city's population, OLS estimates of equation (3) may suffer from an omitted variable bias.[17] Second, monthly data on the population and share of immigrants by city are not available.

The first problem is easily solved by examining changes in prices over time. It was argued that product attributes are constant over the sample period and this implies that their effects disappear when equation (3) is differenced over time. Thus, I exploit the panel structure of the data to get rid of these time-invariant product characteristics. Notice that the store and city effects also disappear after differencing.

First-differencing, however, does not address the lack of monthly data on S_{ct} and L_{ct}. The only time-differencing for which we have immigrants data is for a 12-month

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[16]An alternative specification of the price equation $p_{jict} = ((1+\theta_j)\, I_{ct} + N_{ct})^{\beta_j}\, e^{A_{jict}}$, where I is the number of immigrants and N is the number of natives, results in the same estimated equation after using the approximation $\ln(1+\theta_j)S_{ct} \approx \theta_j S_{ct}$. In this case, $\delta_j = \beta_j\theta_j$. Marginal effects, however, are different. Specification (1) is preferred because the alternative specification does not allow for an immigration effect independent of a market size effect. That is, if $\beta_j = 0$ then there is no immigration effect regardless of the value of θ_j.

[17]To some extent the effects of these characteristics are accounted for by the store dummies (certainly when a store sells a single product in the data). Notice that the sign of the omitted variable bias is not a-priori clear since it is not obvious in which direction, if at all, product characteristics and population size and composition are correlated.

difference, i.e., the December 1990-December 1989 difference, assuming that the share of immigrants is zero on December 31, 1989 in all cities ($S_{c0} = 0$). This, however, is not feasible because I do not have price data for December 1989. I therefore try to get the longest possible difference for each store-product observation. Moving to "long differences" has the additional advantage that it removes part of the month-to-month noise in price changes caused by getting in and out of sales and other promotions.

Let t_{0ij} and t_{1ij} be the first and last month a store i–product j observation is observed in the sample. I compute an average monthly percentage price change during this period. For example, a store appearing for the first time in April 1990 and for the last time in November 1990 will have $t_{0ij} = 4$ and $t_{1ij} = 11$. Recall that the median duration is 6 months (see Table 2). "Long-differencing" equation (3) and dividing by $t_{1ij} - t_{0ij}$ gives the average monthly price change,

$$\frac{\log p_{jict_{1ij}} - \log p_{jict_{0ij}}}{t_{1ij} - t_{0ij}} = \frac{\mu_{t_{1ij}} - \mu_{t_{0ij}}}{t_{1ij} - t_{0ij}} + \pi_j \qquad (4)$$

$$+ \delta_j \frac{S_{ct_{1ij}} - S_{ct_{0ij}}}{t_{1ij} - t_{0ij}} + \beta_j \frac{\log L_{ct_{1ij}} - \log L_{ct_{0ij}}}{t_{1ij} - t_{0ij}} + \Delta u_{jic}$$

where $\Delta u_{jic} = \frac{u_{jict_{1ij}} - u_{jict_{0ij}}}{t_{1ij} - t_{0ij}}$. In going from equation (3) to equation (4) it was assumed that

$$\mu_{jt} = \pi_j t \qquad (5)$$

i.e., each product has a different monthly inflation rate which is invariant over the sample period.[18]

The key regressors in (4), the average monthly change in S and the average monthly percentage change in total population, are unobserved. I measure them as follows. It can be safely assumed that S was zero or very close to it in all cities in December 31, 1989 (see Figure 3). For the remaining months we assume that S grew *linearly* from zero to the value in 31 December 1990, denoted by S_{c12}. That is,

$$S_{ct} = t \frac{S_{c12}}{12} \qquad (6)$$

[18]A completely unrestricted specification for μ_{jt} is theoretically plausible but practically very difficult to estimate in our data because it requires estimation of over 5000 parameters.

for each month $t = 1, 2, \ldots, 12$. Since the monthly increment in S is $\frac{S_{c12}}{12}$ we use $\frac{S_{c12}}{12}$ instead of $\frac{S_{ct_{1ij}} - S_{ct_{0ij}}}{t_{1ij} - t_{0ij}}$ in equation (4).

For the total population we assume a *constant* monthly growth rate,

$$L_{ct} = L_{c0}(1 + g_c)^t \tag{7}$$

where L_{c12} and L_{c0} are the population levels at the end of December 1990 and 1989, respectively. This implies that the growth rate g_c is approximately equal to $\frac{\log L_{c12} - \log L_{c0}}{12}$. Thus, we use $\frac{\log L_{c12} - \log L_{c0}}{12}$ instead of $\frac{\log L_{ct_{1ij}} - \log L_{ct_{0ij}}}{t_{1ij} - t_{0ij}}$ in equation (4).[19]

A few remarks on regression (4) are in order. First, all store-products observations in the same city have the same values of the immigration share and population growth regressors. Thus, we cannot separately identify their effects from the effects of city-specific price trends. In Israel, however, due to its small geographic size and high degree of integration, it is very unlikely that prices exhibit significant city-specific trends over prolonged periods of time. Second, $\frac{\mu_{t_{1ij}} - \mu_{t_{0ij}}}{t_{1ij} - t_{0ij}}$ is the average monthly inflation rate between t_{0ij} and t_{1ij}. Since this varies across store-products we dummify the $t_1's$ and $t_0's$ and enter them separately in the regression after multiplying them by inverse sample duration, $\frac{1}{t_{1ij} - t_{0ij}}$. Finally, notice that the months affected by long-differencing depend on the store's price availability, i.e., on t_{0ij} and t_{1ij}. Since the panel is very much unbalanced in terms of the months in which each store-product observation appears in the sample, there is a lot of variation in the length of the time difference $(t_{1ij} - t_{0ij})$ as well as on the specific months over which the price change is computed.

Because there is no variation in the values of the regressors within cities, identification of the parameters relies on the cross-city variation in S_{c12} and $\log L_{c12} - \log L_{c0}$ only. In particular, all cities started with $S_{c0} = 0$ but evolved differently in terms of

[19] An obvious alternative to the linear interpolation scheme in (6) is to interpolate backwards the number of immigrants in each city using the aggregate (national) monthly growth rate in the stock of immigrants (see the Appendix for details). This would introduce variation over time in S_{ct} which would contribute to the identification of δ. The problem with this approach is that this monthly variation is not based on *actual* city-level data. Thus, I prefer to forgo this source of identification and rely only on cross-city variation in S in December 1990. In any case, this interpolation assumption, as well as a third alternative, are examined empirically in Section 4 where it is shown that the estimated immigration effects are robust to the particular interpolation scheme used.

their absorption of immigrants. Thus, the monthly change in S differs across cities. This cross-sectional variation is used to identify the effect of S on prices.

Finally, because there are 478 products, I adopt a random coefficients formulation and focus on estimating the mean effects δ and β,

$$\begin{aligned} \delta_j &= \delta + \eta_j^\delta \\ \beta_j &= \beta + \eta_j^\beta \end{aligned} \tag{8}$$

I assume

$$\begin{aligned} E\left(\eta_j^\delta | x_{cj}\right) = E\left(\eta_j^\beta | x_{cj}\right) = 0 \\ E\left(\eta_j^\delta \eta_k^\delta | x_{cj}, x_{ck}\right) = E\left(\eta_j^\beta \eta_k^\beta | x_{cj}, x_{ck}\right) = E\left(\eta_j^\delta \eta_k^\beta | x_{cj}, x_{ck}\right) = 0 \text{ for } j \neq k \end{aligned} \tag{9}$$

where $x_{cj} = (S_{c12}, L_{c0}, L_{c12}, t_1, t_0, \pi_j)$.

Assumption (9) says that there is no relationship between the population size and composition in a city and the magnitude of the price response to changes in them. A specific product could be more responsive to immigrants because of product-specific attributes that match the immigrants tastes but this matching is independent of the population and share of immigrants in the city. We also assume that the random component of the coefficients are uncorrelated across products. All the correlation across store-products is captured by the store, city and month effects.

Based on (6), (7) and (8), the estimated equation becomes

$$\begin{aligned} \frac{\log p_{jict_{1ij}} - \log p_{jict_{0ij}}}{t_{1ij} - t_{0ij}} &= \frac{\mu_{t_{1ij}} - \mu_{t_{0ij}}}{t_{1ij} - t_{0ij}} + \pi_j + \delta \frac{S_{c12}}{12} + \beta \frac{\log L_{c12} - \log L_{c0}}{12} \\ &\quad + \Delta u_{jic} + \frac{\eta_j^\delta \frac{S_{c12}}{12} + \eta_j^\beta \frac{\log L_{c12} - \log L_{c0}}{12}}{t_{1ij} - t_{0ij}} + \text{measurement error} \end{aligned} \tag{10}$$

Equation (10) is estimated by OLS after pooling all store-product observations across all stores and products. Notice that each store-product combination has a *single* observation representing its average monthly price change.

Assumptions (9) suffice for $\frac{\eta_j^{\delta}\frac{S_{c12}}{12}+\eta_j^{\beta}\frac{\log L_{c12}-\log L_{c0}}{12}}{t_{1ij}-t_{0ij}}$ to be mean-independence of S_{c12} and $\log L_{c12} - \log L_{c0}$. In order for Δu_{jic} to be uncorrelated with the regressors it suffices to assume that u_{jict} is mean-independent of S_{ct} and $\log L_{ct}$, conditional on the various fixed effects.

This last identifying assumption implies that product-store specific price shocks are not related to the inflow of immigrants to the city and/or to its population size. This is a reasonable assumption if one believes that immigrants do not decide where to settle on the basis of the occurrence of *store-specific* sales. This does not mean that immigrants do not choose to settle in cities with lower or higher than *average* prices. In fact, models of urban theory posit that the decision to live in a particular city depends, among other things, on the amenities offered by the city. In our particular case, immigrants may be attracted to cities with particular traits, implying a correlation between S and μ_c. If immigrants are attracted to cities with large employment opportunities and high levels of amenities – and these are associated with higher than average prices – then we may expect a positive correlation between S and μ_c.[20] Conversely, if immigrants are attracted to cities where the cost-of-living is lower, then S and μ_c may be negatively correlated. Importantly we make no assumptions on the correlation between the city effects and the city's population and share of immigrants. In fact, we make no assumptions on the correlation between any of the "fixed effects" affecting the price level and S or L.

Assuming constant growth rates in the population and, implicitly, in the number of immigrants leads to regressors with measurement errors. In general, long difference equations have the advantage of reducing biases due to measurement errors in the regressors (Griliches and Hausman, 1986). This is particularly true in our case. Only when $t_1 = 12$ and $t_0 = 1$ the regressors in (4) would be measured without errors (if S was zero in January 1990). The longer the time-difference, the closer the regressors match the available data and measurement errors are less severe. When reviewing the estimates in Section 4, one should recall that the presence of measurement errors usually attenu-

[20]Using data from previous immigration waves (1969-72), Beenstock (1997) reports that immigrants tend to move for job-related reasons during their first year in Israel but that internal mobility is unrelated to job-status in later years.

ate the OLS estimator towards zero, which works towards finding estimated effects not significantly different from zero.

The remaining issue is the estimator's covariance matrix. First, because of the presence of product, store and city effects in the price level equation, the price shock u_{jict} could, as a first approximation, be treated as uncorrelated across products, stores and cities. Second, because the data used to estimate equation (10) is a *single* observation per store-product combination, I make no assumptions on the serial correlation in u_{jict}. Third, notice that the random coefficient assumption (8) induces a correlation among prices of the same product across stores. Thus I allow for arbitrary correlation of the disturbance in equation (10) across prices of the same product (in different stores), but assume zero correlation between prices of different products. Practically, this requires clustering the standard errors at the product level. Finally, if there is a time-varying, city-level component in u_{jict} (e.g., weather) then Δu_{jic} will be correlated within cities. Not accounting for this correlation tends to bias the estimated standard errors downwards, particularly when the regressors are highly correlated within cities as is the case here. Clustering at the city level solves this problem.

4 Empirical Results

Regressions (1) and (2) in Table 3 present the estimates of δ and β from equation (10). The sample consists of 16,038 store-product observations. In the first column we omit the immigrant share in order to test the extent to which prices are correlated with the population level as suggested by the short-run, standard competitive model. We find that population size actually has a negative, but insignificant, effect on prices.

In column (2), the share of immigrants is added to the regression. The point estimate of δ indicates that a 1 percentage point increase in the share of immigrants in a city, holding population size constant, decreases prices by 1.44 percent, while a 1 percent increase in population, holding its immigrant share constant, raises prices by 1.35 percent. These are strong and precisely estimated effects. Notice that omitting the immigrant share leads to a serious underestimation of the population effect.[21]

As mentioned in Section 4, the immigration effect is identified by variation in S_{c12} across cities. Because S_{c12} is at the city-level, it is appropriate to match its cross-city variation to variations in city-average price changes. We do this in two steps. First, we average equation (10) to the city-product level, eliminating the variation in price changes across stores within a city. Then we average further up to the city level, eliminating the variation in price changes across products within a city. Notice that aggregating up from store-level data is the correct way to do this so as not to confound store-specific price changes with price changes due to changes in the identity of the stores over time.

Regressions (3) and (4) present OLS estimates from the city-product level regressions; the dependent variable being the average price change of product j across stores in city c. Aggregating over stores gives 8,443 city-product observations.[22,23] The estimates are almost the same as those obtained using data at the city-product-store level, but slightly less precisely estimated because of the lower number of observations.

Aggregating further up to the city-level, reduces the number of observations to the 52 cities. Here, δ is essentially estimated by regressing the "between long-differenced" regression: the average monthly price change in a city (averaged across all stores and products in each city c) regressed on the city-level immigrant's share and population growth (see Wooldridge (2003) and Donald and Lang (2001)). The estimated δ and β in column (6) are very close to the previous estimates.

Notice that when aggregating all product observations in a city, $\sum_{j \in J_c} \pi_j$ will differ across cities because J_c, the set of sampled products, differs across cities. Since this cannot be controlled for in the regression (e.g., via city dummies) the estimates of

[21]The simple correlation between population growth and S across cities is about 0.9, but that between population levels and S is negative (-0.2).

[22]These are unweighted estimates. We could improve efficiency by weighting the aggregate observations by the inverse of the standard error in the group (the stores selling the same product in the same city), provided there is homoskedasticity within the group.

[23]We first created the interactions between the dummies for the $t_1's$ and the $t_0's$ and $\frac{1}{t_{1ij}-t_{0ij}}$ and then averaged across stores. The alternative: averaging the $t_1's$, $t_0's$ and $\frac{1}{t_{1ij}-t_{0ij}}$ across stores and then dummifying results in almost identical estimates of δ and β.

δ and β may be biased. But the finding that the point estimates of δ and β are very close to the ones obtained when controlling for product effects, suggests that the possible correlation between the set of products sampled and the regressors is not a problem.

The similarity of the estimates across the different aggregation levels emphasizes that identification of the size and composition effects is indeed obtained from the cross-city variation in the growth rates of S or, in other words, from the spatial differences in the pace at which immigrants settled in Israel.

To trace the price effect of the arrival of a new immigrant at a city we differentiate expected log price, equation (3), with respect to the number of immigrants (I), taking into account that $L = I + Natives$,

$$\frac{\partial E(\log p|S, L))}{\partial I} = \frac{1}{L}\left[(1 - S) \times \delta + \beta\right]$$

Immigrants have two opposing effects on prices. They increase overall demand and this increases prices ($\beta > 0$), but they also change the composition of demand in ways that decrease price ($\delta < 0$). Thus the effect of immigrants on prices is smaller in magnitude than that of non-immigrants. Using a simple average of the estimates in Table 3, columns (2), (4) and (6), we have

$$\frac{\partial \widehat{E(\log p|S, L))}}{\partial I} = \frac{1}{L}\left[-(1 - S)\, 1.62 + 1.37\right]$$

which implies that immigrants have a net negative effect on prices as long as $S < 0.15$.

Since there are no cities in 1990 with shares above 15 percent we conclude that immigration had a negative net effect on prices.[24] Of course, we should not expect to observe absolute decreases in prices because the net negative immigration effect is just a partial effect. After all, many other factors not accounted for by the regression also affect prices, while the natural increase in the native population exerts a positive push on prices. It is therefore of interest to note that 12 and 41 percent of all 16,038 average monthly price changes in the sample were, respectively, negative or zero, at a time when the average CPI monthly increase was 1.4 percent.

[24]Using the estimates from column (2) immigration has a negative effect as long as $S < 0.065$.

Another point to be emphasized is that the estimated immigration effects are obtained after controlling for the selection of immigrants into cities. This can be further appreciated by comparing the estimates in Table 3 to the estimates of the price equation (3) estimated in levels in Table 4.[25] When only population growth is included, besides month, product and product-specific inflation rates, we estimate a positive and significant, yet very small, population elasticity.[26] In column (2), the share of immigrants is added to the regression. The effect of population size on prices remains unchanged. The point estimate of δ indicates that a 1 percentage point increase in the share of immigrants is associated with a *higher* level of prices of about 0.7 percent, holding population size constant. This effect is the opposite of the one estimated from the differenced regressions. The "levels" regressions are, of course, misspecified because they do not control neither for store or city nor brand effects and, as pointed out in Section 3, there are good reasons to suspect that omitting these controls could generate biased estimates of δ and β.

In column (3), store dummies were added to the regression.[27] The change in the estimated effects is quite dramatic. Estimated δ changes sign and the effect of population size on prices increases by a factor of almost 60! Now, a 1 percentage point increase in the share of immigrants, holding population size constant, decreases prices by almost 1.3 percent, while a 1 percent increase in population, holding its immigrant

[25]The monthly levels of S and L in each city are computed using (6) and (7).

[26]Standard errors clustered at the product level allow for arbitrary serial correlation within stores in u_{jict}. Because L and S change over time standard errors are also clustered at the city-month level.

[27]Joint identification of city and store effects, however, is not possible. Whereas store effects are identified when there are two or more stores selling the same product in the same city, city effects would be identified if we had data on the *same* store selling the same product in two different cities. Since this does not happen in the data, μ_c cannot be estimated jointly with μ_i (the store and city dummies are perfectly collinear). In theory it might be possible to identify the city effects if we had data on a chain of identical stores operating in different cities. Because the focus of the paper is on the effect of population size and composition I do not see this as a serious limitation.

I prefer the "store effects" version of equation (3) because they allow for greater flexibility in explaining the price data. Using city instead of store dummies restricts all stores in the same city to have the same, time-invariant, effect on prices. Moreover, to the extent that these store effects are correlated, the estimated store effects also pick up part of the city effects. In any case, using city dummies gives a somewhat smaller estimate of δ, -0.009 (0.0046). The estimated β, however, is a third the size of the ones previously obtained, 0.452 (0.50).

composition constant, raises prices by 1.2 percent. These are almost the same estimated effects as those obtained from the long-differenced regressions in Table 3. The change in the estimated effects is consistent with the location of immigrants to places with more amenities and employment opportunities which are also more expensive (large positive store effects).

A way of verifying that the immigrants' share is picking up a demand change is to compare the response to changes in S across different product groups. We would expect to find a stronger immigration effect in products where immigrants represent a larger share of the market because the change in demand would be perceived to be larger in these products. There are 36 product groups in the sample encompassing the 478 individual products. These groups are determined by the CBS classification of products. Table 5 presents results obtained by interacting the immigrant's share and population regressors with a product group dummy. The table reports only the estimated coefficient of δ for each group (and not just the contrast with the reference group) and its standard error, sorted in ascending order starting with the significant ones.

Notice that the immigration effect is negative in 32 out of the 36 product groups but only 10 products have significant negative estimates (at the 10 percent significance level or less). These results show that the negative immigration effect is not specific to particular products.[28] We argued above, however, that this effect should be stronger in markets where immigrants' share is larger. Fortunately, the specific religious and sociological characteristics of Israel provide us with a natural market where immigrants constitute a major force: pork products. Pork products were sold in Israel for a long time but the market was relatively small. The arrival of the largely non-kosher FSU immigration, which was also familiar with pork products, generated a disproportionate increase in the demand for pork products.[29] Indeed, pork products exhibit a very strong

[28] Formal tests of the hypothesis that all interaction effects are zero have a p-value of 0.41 for δ and 0.39 for β. Thus, the data does not support systematic differences in parameters across products justifying, to some extent, the assumption that all deviations in product coefficients are random.

[29] These products are not sold in the standard supermarkets or grocery stores because they are non-kosher. They are sold in special non-kosher butcher shops. The visible increase in the number of these stores during the 1990s is attributed to the FSU immigration.

and significant negative immigration effect. The same could be said about music and alcoholic beverages.[30]

About of 2/3 of all the immigrants arriving in 1900 arrived in the second half of the year. However, many of the those arriving during the first half of the year were accommodated in Absorption Centers where they lived and studied Hebrew. Their basic necessities (basic food and lodging) were taken care off. On the other hand, most of those arriving during the second half of 1990 (and later on) went through the "direct absorption" method: they received a subsidy and had to rent a standard apartment in the private market. Thus, the change in demand was larger during the second half of the year both because of the smaller number of immigrants and because those that arrived did not fully integrate into the market economy until a few months later. We should then expect the downward pressure on prices to be stronger during the second half of the year. I reestimated regression (2) in Table 3 for the first and second half of 1990 separately: the regressors are the same but the average monthly price changes are computed using data for the January-June and the July-December periods. The immigration effect during the second half of the year is -0.0175 (s.e. 0.007) about twice its size during the first half of the year, -0.009 (s.e. 0.006). The total population effect is also not significant in the first half of the year as would be expected if the early immigrants did not integrate into city life right away.

In sum, immigration had a moderating effect on inflation in 1990 because the pace at which prices increased was slower than it would have otherwise been: a 1 percentage point increase in the share of immigrants in a city decreases prices by 1.4-1.8 percent. Since stores cannot price discriminate, the whole population benefits from the added

[30]It is not straightforward to match consumption data to the product groups defined by the CBS for the Consumer Price Index. Nevertheless, data from the Household Expenditure Survey (1994) for 1992/1993 is informative on the share of FSU immigrants in different types of expenditures. The data reveal that FSU immigrants' share in total consumption, as well as in food consumption, was 8 percent. However, their share in the expenditures chicken and beef products (including pork products) was 19 percent, in alcoholic beverages it was 16 percent, in durable culture and entertainment products (including music) it was 16 percent, in fish it was 11 percent and in meat and poultry it was 9 percent. These are product types associated with the products at the top of the list in Table 5. On the other hand, FSU immigrants' share in the expenditure on linen was 3.3 percent, in toys and games it was 5.2 percent and in tea, coffee and chocolate milk it was 6.7 percent. The latter are product types associated with the products at the bottom of the list in Table 5.

consumer surplus generated by the price decreases. At the aggregate level, prices were $5.6-7.2$ ($1.4\times4-1.8\times4$) percent lower than what they would have been in the absence of the FSU immigrants. Since private consumption (excluding housing) was about \$23,000 per household during 1990, an upper bound to the gain in consumer surplus due to the FSU immigration amounts to a significant \$1,290-\$1,650 per household.[31]

4.1 Robustness Checks

In this section I examine the robustness of the previous results to variations and to extensions of the baseline equation (10) and its estimates in Table 3.

The estimates are robust to the interpolation assumptions made in Section 3. Two cases are considered. In the first case, instead of assuming a linear trajectory for S and a constant monthly growth for L, I assume that the monthly increments to the number of immigrants and to total population in each city were constant over time (Method 1 in the Appendix). The estimated parameters using this alternative interpolation appear in columns (1), (3) and (5) of Table 6. In the second case, I assume that in each city the number of immigrants grow according to the monthly aggregate growth rate. I then deduce backwards, from the December 1990 levels, the number of immigrants and compute the share of immigrants S_{ct} in each month. These estimates are in columns (2), (4) and (6) of Table 6.

These two alternative assumptions imply time-varying immigrant shares which adds another source of identification. This source of identification, however, is problematic because it is fictitious: there are no actual data on the monthly changes in S and L. In any case, the estimates of δ are significantly negative and, except for those in column (2) and maybe (4), are of the same order of magnitude as the estimates in Table 3. This suggests, again, that the identification of the parameters is essentially driven by the cross-city variation in immigration shares and population growth.

[31] This is an upper bound because the housing market was ignored in this calculation. It is unlikely that these consumer gains were wiped out in the following year(s) because long-run increases in supply (through capacity expansion of current stores and entry of new ones) would have contributed to further decreases in price. Notably, CPI inflation in 1991 was the same as in 1990 and from 1992 onwards it was significantly lower.

Table 7 replicates Table 3 except that it is based on the one-month difference version of (3). There are more observations now – 73,926 store-product-month observations – because each store-product combination is observed in several months. This would have increased the precision of the estimators were not for the fact that the dependent variable is now much noisier.[32] Consequently, the gain in precision is not as large as could have been expected from the almost 5 times increase in the number of observations. The point estimates in columns (2) are remarkably similar to those in column (2) of Table 3. Columns (3) and (4) present estimates of δ and β, when the dependent variable is the monthly price change averaged over stores for a given product, month and city. This gives 53,619 observations. Again, the results are similar to those in the corresponding columns of Table 3.[33] Columns (5) and (6) in Table 6 show the estimated δ and β obtained after aggregation to the city level. That is, we average price changes over stores, products and months in the same city. City-average price changes are regressed on the monthly change in S and on the monthly population growth rate. Both estimates are about half the size of the previous ones, but while the estimate for δ remains significantly negative that of β is not significantly different from zero.[34]

In Table 8, I use an instrumental variable estimator to allow for the possibility that immigrants keep track of price deviations (the $u'_{jict}s$) and factor them into their choice of city. The instrument is the share of Russian immigrants in the city reported in the 1983 Population Census. I instrument only for the immigrant share, and treat population growth as exogenous in this regression, which is clearly not satisfactory. The

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[32]The root mean squared error of the regression in column (2) increases from 0.041 in Table 3 to 0.089 in Table 7.

[33]The comparison between the estimates in Tables 7 and 3 may serve as a informal specification test of the identifying assumptions since it suggests that the *monthly* innovations to the price shocks in the regressions in Table 7, $u_{jict} - u_{jict-1}$, and the time-averaged innovations appearing in the regressions in Table 3, $\frac{1}{t_{1ij}-t_{0ij}} \sum_{\tau=1}^{t_{1ij}-t_{0ij}} \left(u_{jict_{0ij}+\tau} - u_{jict_{0ij}}\right)$, are equally correlated with the regressors, which is unlikely unless this correlation is indeed zero in both cases.

[34]A weighted OLS regression with weights equal to the inverse of the variance of the average price change in the city gives better results: $\widehat{\delta} = -0.0117$ (s.e. 0.0036) and $\widehat{\beta} = 0.9797$ (s.e. 0.3823). For comparison, the WLS estimates in the city-level long-difference regression (Table 3, column (6)) are $\widehat{\delta} = -0.0152$ (s.e. 0.0050) and $\widehat{\beta} = 1.2503$ (s.e. 0.5793).

estimate of δ and β are very similar to those in Table 3, except for those at the city-level where they are half the size. Standard errors are, of course, much higher in the IV regressions making the estimates less significant than in Table 3.[35] The estimates of δ are still negative and of reasonable size.

Table 9 is an attempt to control for spatial effects. I implicitly defined the boundaries of the relevant markets as those given by the city limits. This is unduly restrictive because inter-city distances in Israel are not large and therefore immigrants in one city can easily make their weekly purchases in a nearby city. It follows that the change in demand in a city should also take into account the immigrants in the city's surrounding area. As a first approximation, I divided the cities into four metropolitan areas – Jerusalem (1 city), the Northern area (22 cities), the Central area (23 cities) and the Southern area (6 cities) – and, for each city c, I computed the immigrant share in the metropolitan area where each city c is located (not including city c). This new variable (ΔS^{metro}) is added to the regressors in equation (10). The estimates of δ are again very similar to those in Table 3.[36] The estimates of the δ^{metro} coefficient all have negative signs but are not significantly different from zero, maybe because there is not much cross-city variation in this regressor. In any case, the estimated coefficients of δ^{metro} are much smaller than those of δ which means that "own" effects are, not surprisingly, more important than "neighboring" effects. Spatial search effects do not seem to be that important in this sample.

FSU immigrants did not settle in Arab cities. On the other hand, most of these cities had above average inflation in 1990 (see Table 1). Thus, the estimated negative relationship between immigration and prices could be driven by these few cities. However, when the six Arab cities are excluded from the regression, the estimated effects remain essentially unaffected.[37]

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[35] The t-values of the instrument in the first-stage regression in columns (1), (2) and (3) are 1.8, 3.0 and 3.5, respectively, using standard errors clustered at the city level.

[36] The regressions in Table 8 do not include observations for Jerusalem because Jerusalem is a single metropolitan area (ΔS^{metro} is not defined). Redefining the metropolitan share to include the city (and thus including Jerusalem in the regression) generates almost identical estimates of all parameters.

[37] For example, the estimates of δ and β corresponding to regression (2) in Table 3 are -0.0128 (s.e.

Finally, one may conjecture that the arrival of immigrants may initially decrease prices but further increases in S may have smaller effects because prices are already close to their competitive level. In order to capture this nonlinear effect I added S^2 to the specification but its effect, although positive, is very small and not significantly different from zero. The marginal effect of the immigration share on prices is constant in this sample. The estimated δ and β remain unchanged.

In sum, the estimates of the effect of the immigration share on prices in Table 3 are robust to various modifications and extensions. In fact, it is quite remarkable that, in most cases, the estimates of δ are numerically very similar to those in the baseline specification implying that a 1 percentage point increase in the share of immigrants in a city decreases prices by 1.4-1.8 percent.

5 Explanations

In the standard perfectly competitive model when demand increases prices should increase, at least in the short run, because of increasing marginal costs of production.[38] Yet, the results in this paper accord with a growing body of empirical evidence pointing to the opposite phenomenon: retail prices appear to fall during periods of high demand (Warner and Barsky, 1995; MacDonald, 2000; Chevalier et al., 2002). These findings, however, can be easily accommodated when we depart from the perfectly competitive paradigm. In this Section, I review some of the theoretical explanations and assess their relevance to the findings in this paper.

Perhaps the first explanation that comes to mind is that the increase in demand led to the opening of new stores which intensified price competition resulting in lower prices. This, however, cannot be the whole story because the empirical analysis focuses on the short run (the year 1990) during which entry of new stores was likely to be a minor phenomenon (see Section 2.1).

= 0.004) and 1.257 (s.e.= 0.383), respectively. Other results available upon request.

[38] In the long run, after the number of firms adjusts, price should return to its original level under constant returns to scale and barring general equilibrium effects.

Rotemberg and Saloner (1986) argue that tacit collusion on a high price is more costly to maintain during periods of high demand. When demand is high, the temptation to undercut prices and increase market share is highest. This is particularly true if the change in demand is temporary because the gains from deviating during a high demand period are larger than the future losses due to the low prices charged by rivals as punishment for the deviation. For this reason the Rotemberg-Saloner model is better suited to analyze price fluctuations due to temporary shocks or to cycles in demand such as weekends and holidays (Warner and Barsky, 1995; Chevalier et al., 2002) rather than to the permanent shift in demand caused by the massive arrival of the FSU immigrants. Nevertheless, in the beginning, the arrival of FSU immigrants may have been perceived as a temporary event, particularly from a city's point of view, since there was a lot of uncertainty regarding the future inflow of new immigrants as well as the immigrants' final place of residency.[39] The Rotemberg-Saloner model would predict that cities that *increased* their population due to immigration should have *lower* prices on average. This prediction is not borne out by the data. As shown in Table 3, increases in population either increase prices or do not significantly decrease them, depending on whether demand composition is or is not controlled for.

In fact, the key to understanding the negative effect of immigration on prices is that the increase in demand caused by the arrival of the FSU immigrants led also to a change in the *composition* of demand. If the consumption behavior of FSU immigrants differed from that of natives this could have affected prices in non-trivial ways.

Bils's (1989) model of pricing in a market where consumers develop some attachment to products they have previously purchased is an appropriate example. The model shows that if demand is high because of a high inflow of potential new buyers who are not attached to the firm's products, firms will lower their markups in order to attract these new buyers, trading-off the objectives of exploiting past customers and attracting

[39] On the internal migration of immigrants see Beenstock (1997). Based on data for Israel during 1969-72, Beenstock reports that the propensity to move during the immigrants' first year in Israel ranges from 39 percent for those immigrants that located initially in the North of Israel to 16 percent for those that located initially in the Central region of Israel.

new ones. It is a mild assumption to assume that FSU immigrants did not have strong brand attachments upon arrival in Israel. This model would predict that cities where the influx of immigrants is larger should exhibit milder price increases, or even price decreases.

The basic prediction of the Bils model is consistent with the finding of a negative immigration price effect. In fact, any model where, for whatever reason (e.g., lower income), new immigrants have higher price elasticities than the native population is capable of predicting a negative correlation between price and demand changes. In these models, stores find it optimally to reduce prices when consumers, especially the new buyers, have perfect information about prices. This is a strong assumption in light of the extensive empirical literature on price dispersion.[40] When consumers do not have full information about prices and acquiring information about them is costly, stores develop some market power and are consequently less motivated to reduce their prices. Indeed, Diamond (1971) showed that prices will converge to the monopoly price. It is the presence of a mass of consumers with negligible search costs that can discipline shoppers to lower their prices. This is the role played by the FSU immigration.

Data on shopping habits of consumers are available in the Time Budget Survey (1995) conducted in late 1991 and early 1992. FSU immigrants are identified by their country of immigration and by requiring that they immigrated to Israel after 1989. As seen in Table 10, time spent shopping per day averages to 26 minutes for immigrants and just to 15 minutes for natives. Most individuals did not shop during the day they were sampled but, among those shopping, immigrants spent markedly more time shopping than non-immigrants.[41] Although time shopping is not exactly equivalent to time spent searching for low prices it certainly is among the measurements closest to the ideal concept.

[40] See Lach (2002) for evidence on the existence and persistence of price dispersion in Israel.

[41] The difference remains after controlling for individual and household characteristics. An OLS regression of time shopping on an immigrant dummy, age, gender, an employment indicator and on household size and income, gives an estimated coefficient for the immigrant dummy of 9.7 minutes with standard error 2.7.

There are also sound theoretical reasons in support of the notion that immigrants search more than their native counterparts. The familiarity of the initial wave of FSU immigrants arriving in Israel during 1990 with a modern market economy was limited (the economic reforms in the Soviet Union –*perestroika*– started in 1987). Learning about the different ways in which a market economy operates can be thought of as a process of search. The immigrants visited the stores and learnt about the huge variety of goods and services offered in the Israeli market, particularly in relation to their previous experience in the FSU. In particular, they learnt that the same products are sold at different prices in different stores. The existence of price dispersion constitutes a powerful incentive for immigrants to engage in search for the stores having the best combination of product characteristics and prices. Processing this new information and matching the new options to their individual preferences takes time and effort. But the alternative cost of this time and effort was relatively low for FSU immigrants because most of them were not gainfully employed during the first few months following their arrival in Israel. At the time of the 1990 Labor Force Survey, 81 percent of the immigrants that arrived during 1990 were *not* part of the labor force, and among those in the labor force 53 percent were unemployed.[42] The new immigrants had a lot of free time, and invested their time and effort in learning the language and familiarizing with the market economy in Israel. Thus, lower search costs would imply that immigrants engaged in search more extensively than the native Israelis.[43]

What happens to prices when the new immigrants search more intensively for bargains that the native population? A precise answer is provided by Stahl's (1989) model of consumer search.[44] In this model a fraction μ of consumers has zero search

[42]The participation rate of Israeli-born persons was around 57 percent and their unemployment rate was 11 percent. In 1991, 54 percent of the immigrants arriving in 1990 and 1991 were not in the labor force, and among those in the labor force 38 percent were unemployed.

[43]Fishman and Simhon (2005) emphasize the direct role that changes in the distribution of income can have in generating search because the search costs for low-income consumers are lower than for high-income consumers. Thus, an inflow of low-income consumers would increase search in the market.

[44]See Brown and Goolsbee (2002) for a recent empirical examination of the model's implications and Janssen and Moraga-Gonzales (2004) for a recent exposition.

costs. These consumers – called the "shoppers" – will eventually get informed about the stores charging the lowest price of an homogenous product. The other type of consumers have positive search costs. Consumers search sequentially with perfect recall and stop searching when they find a price below their reservation price. The shoppers sample all prices and buy only from the lowest priced store. Identical stores choose their prices taking into account consumer search behavior. In the Nash equilibrium, stores choose their prices from a price distribution rather than from pure strategies. In equilibrium, the shoppers will pay a low price, while the remaining consumers shop randomly. In this fashion, price dispersion is generated as an equilibrium phenomenon. Stahl shows that as more search is conducted, i.e., as the proportion μ of shoppers increases, stores will compete more fiercely by lowering their prices. Intuitively, it pays to deviate downwards because stores that deviate will get all the shoppers. This will result in a distribution of prices that shifts monotonically from the unique monopoly price when $\mu = 0$ towards the unique competitive price when $\mu = 1$. Along the way, the expected price falls monotonically.

If we identify the arrival of immigrants with an increase in the share of shoppers μ then Stahl's model predicts a negative relationship between expected price and the share of immigrants.[45] This prediction is clearly consistent with the results in Table 3.[46] What differentiates this model from Bils's (1989) model, or any other model where price dispersion is ruled out a-priori, is the implication regarding the effect of the arrival of new immigrants on price dispersion. In Stahl's (1989) model, when the fraction of shoppers increases towards one price dispersion first increases, as the market moves away from the monopoly price, but eventually decreases as the equilibrium moves towards the unique competitive price. That is, in contrast to the average price, price dispersion across stores

[45]The important point in Stahl's model is not that search costs are zero but that there is a group of consumers who are fully informed about prices in different stores. Stahl's prediction is robust to the model's assumptions. For example, the earlier models along the "bargains and ripoffs" line generate two-price distributions where an increase in the proportion of consumers with low search costs induces an increase in the proportion of stores selling at the low price. Thus, average price also declines.

[46]In Stahl's model, marginal cost of production is constant and therefore demand size does not affect prices, only its distribution among shoppers and non-shoppers does. To make the model compatible with the data one would need to have increasing marginal costs.

does not decrease monotonically with the amount of search. Brown and Goolsbee (2002) provide empirical evidence on this non-monotonicity in life insurance price dispersion as a function of the share of people researching insurance prices in the Internet. Here, I present similar findings.

For each month and product, I calculated the standard deviation of log price across all stores with non-missing prices in each city. Then, for each product and for each city, I computed the simple average of these standard deviations over all 12 months.[47] This measure of standard deviation captures price dispersion within month and product only, i.e., it excludes dispersion in prices due to changes in prices over time and across products. In 15 cities there are no products that are sampled in more than one store and therefore price dispersion could not be estimated. That is, in 37 cities I have estimates of price dispersion by product. First, I regress these standard deviations on the logarithm of population in each city to estimate a residual price dispersion unrelated to population size. I then use these residual standard deviations to estimate an average (over products) standard deviation by immigrants' share (i.e., by city) using Fan's (1992) locally weighted regression smoother.

In Figure 6, I graph these average standard deviations against the share of immigrants in the city. The graph is remarkably similar to that in Brown and Goolsbee (2002). Price dispersion across stores first raises with the share of immigrants until the immigrants' share reaches almost 5 percent and then declines. This suggests that cities with large immigration shares have prices closer to their competitive equilibrium level. Importantly, the empirical evidence is consistent with this non-trivial prediction of search models, reinforcing the belief that the immigration effects reported in Table 3 do indeed reflect the effect of search on prices.[48]

[47]Weigthing the initial standard deviations by the relative number of stores used in each month's computation does not affect the results.

[48]The same non-monotonic relationship was also found when using the interquartile range instead of the standard deviation.

6 Conclusions

This paper examines what happens to prices following an increase in demand. The exogenous increase in demand comes from the unexpected arrival to Israel of almost 200,000 FSU immigrants during 1990, representing 4 percent of Israel's population. Essentially, I trace the effect of the arrival of FSU immigrants into a city on prices of products sold in the city. The variation in the share of immigrants across cities was large and I use this variation to identify the immigration effect. The data are monthly, store level prices on 478 products sold by 1300 stores in 52 cities across Israel during the year 1990.

The main empirical finding is that immigration had a moderating effect on prices during 1990, controlling for the selection of immigrants into cities and for population size. A 1 percentage point increase in the share of immigrants in a city decreases prices by about 1.4-1.8 percent, holding city population constant. Even when the increase in population is accounted for, the overall effect of immigration on prices remains negative although its magnitude is reduced (in absolute value). The negative immigration effect holds for almost all product groups, and is stronger in products where immigrants have a larger share of the expenditure. It is also stronger during the second half of the year when 2/3 of the immigrants arrived. Thus, the downward effect on prices is stronger when demand increases are larger. The estimates imply an upper bound to the gain in consumer surplus between $1,290 and $1,650 per household in 1990.

The key to understanding why increases in demand lead to lower prices, or to milder price increases, is that immigration increased not only the size of demand but also its composition. The negative effect of the immigration share can be explained by the new immigrants searching more intensively for lower prices than the native population. I present evidence supporting this view. An alternative explanation based on the new immigrants having higher price elasticities than the natives cannot be ruled out, but it is an incomplete description of what happened since it does not address the non-monotonic relationship between price dispersion and the share of immigrants.

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Appendix: Alternative Interpolation Schemes

This appendix presents the two alternative interpolations used in Table 6.

Let I_{ct} be the unknown number of immigrants in city c in month $t = 1, 2, \ldots, 12$. We only know I_{c12} for each city.

Method 1

Assume that the number of immigrants was zero in December 1989, $I_{c0} = 0$. I estimate I_{ct} as follows

$$\begin{aligned} I_{ct} &= I_{ct-1} + \Delta_c \qquad t = 1, \ldots, 11 \\ &= I_{c0} + t\Delta_c \end{aligned}$$

where $\Delta_c = \frac{I_{c12} - I_{c0}}{12}$ is the average monthly increment in I during 1990.

The same procedure is used for the total population except that its known nonzero value in December 1989, L_{c0}, is used.

Method 2

Let g_t be the aggregate growth factor between period $t-1$ and t in the aggregate number of immigrants I_t,

$$g_t = \frac{I_t}{I_{t-1}}, \qquad t = 1, 2, \ldots, 12$$

The known values of g_t, together with I_{c12}, are used to "backcast" the number of immigrants in any city c,

$$I_{ct} = \frac{I_{c12}}{g_{12} \cdots g_{t+1}} = I_{c12} \left(\frac{I_t}{I_{12}} \right), \qquad t = 1, 2, \ldots, 11$$

since $g_{12} \ldots g_{t+1} = \frac{I_{12}}{I_t}$. Note that I_{ct} can be very different from zero in December 1989.

The immigrant share at time t is then approximately

$$S_{ct} = \frac{I_{ct}}{L_{ct}} \approx S_{c12} \left(\frac{I_t}{I_{12}} \right) \left(\frac{L_{c12}}{L_{c0}} \right)^{\frac{12-t}{12}}$$

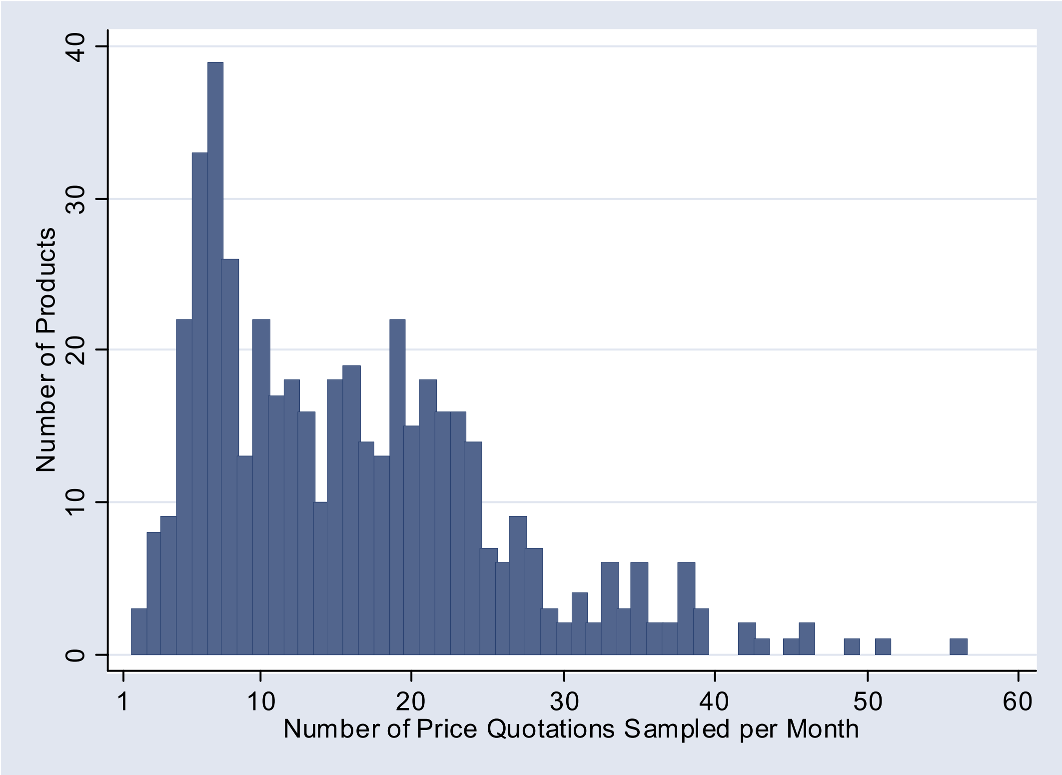

Figure 1: Distribution of Price Quotations per Product

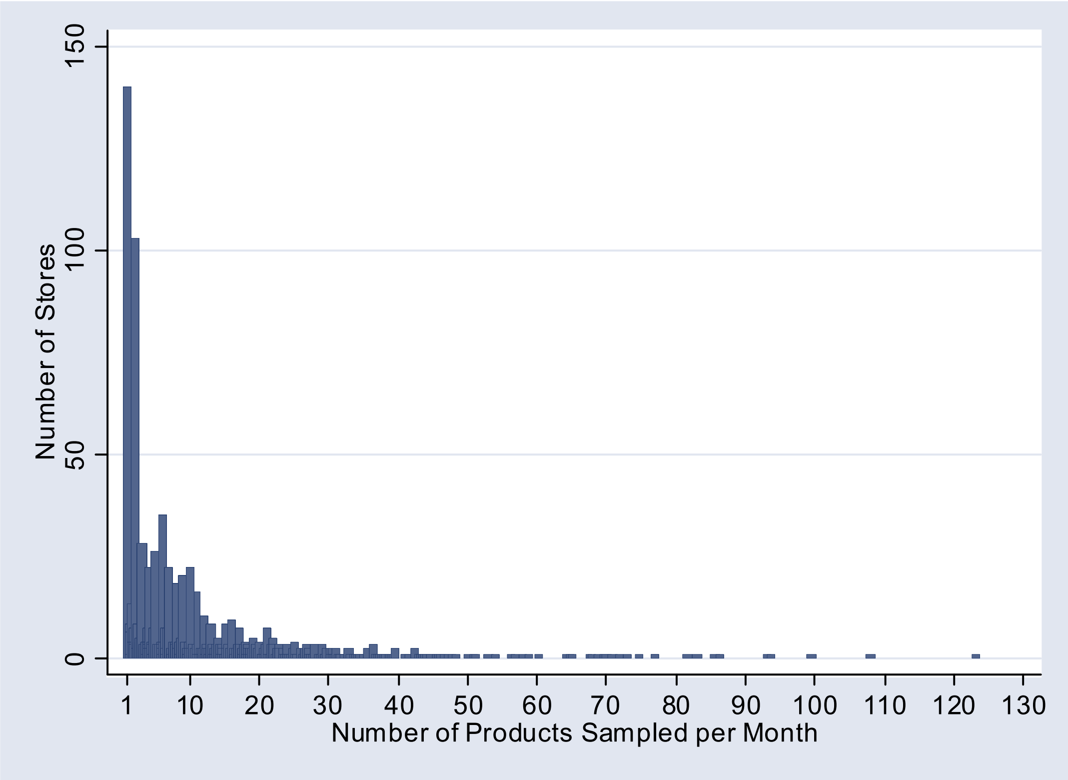

Figure 2: Distribution of Number of Products per Store

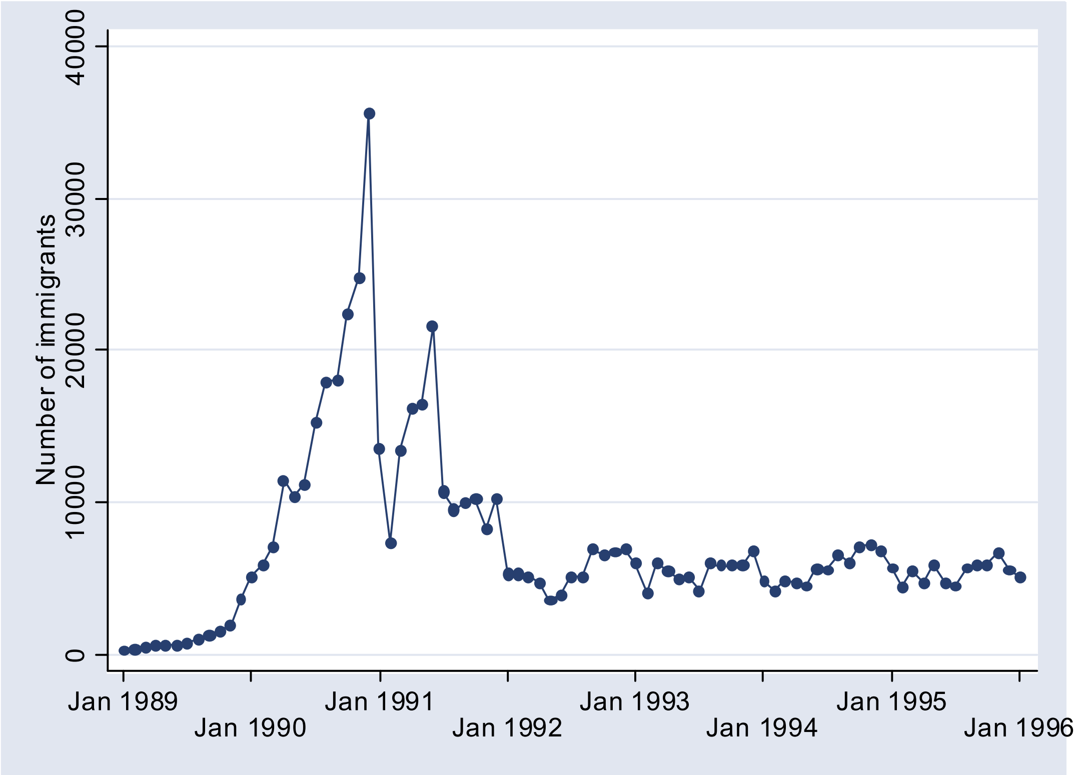

Figure 3: Monthly Flow of FSU Immigrants to Israel

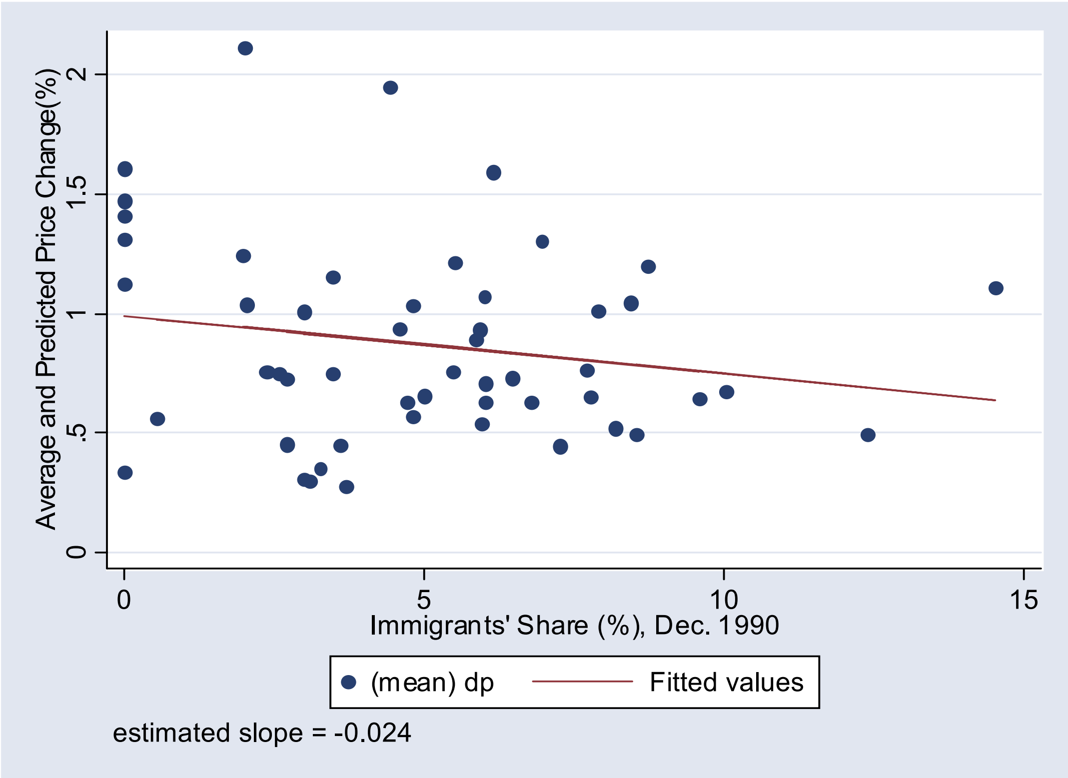

Figure 4: Monthly Price Changes and Immigrants' Share

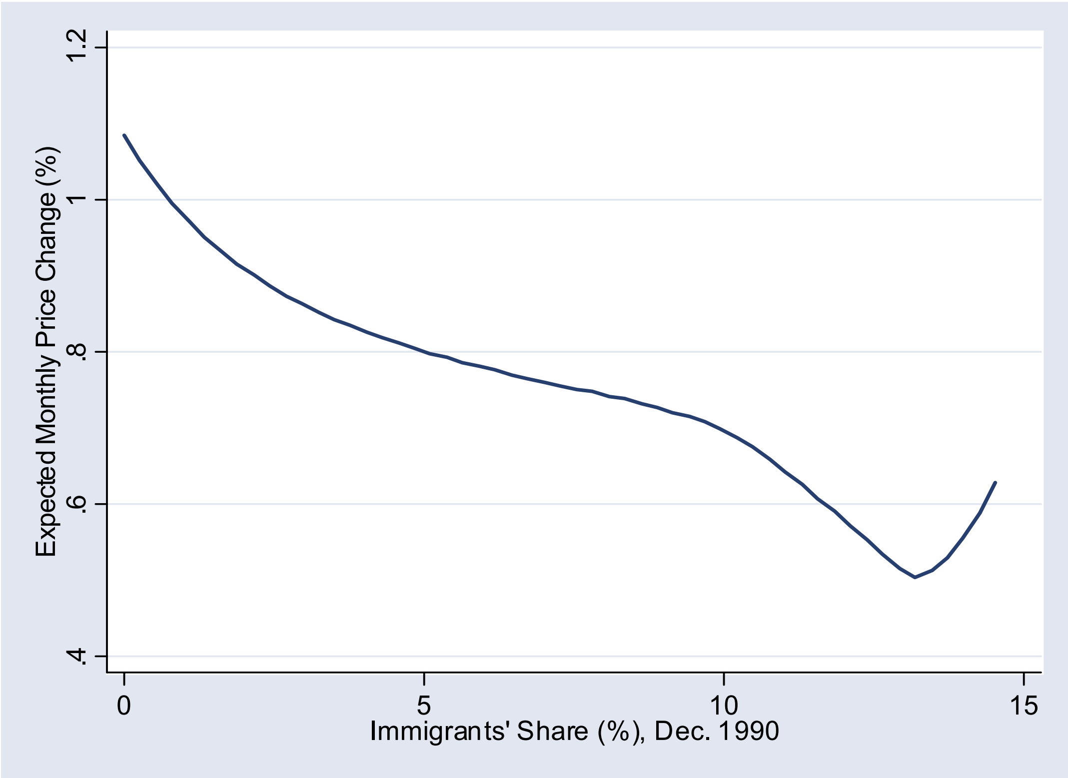

Figure 5: Expected Price Change Conditional on Immigrants' Share in Dec. 1990

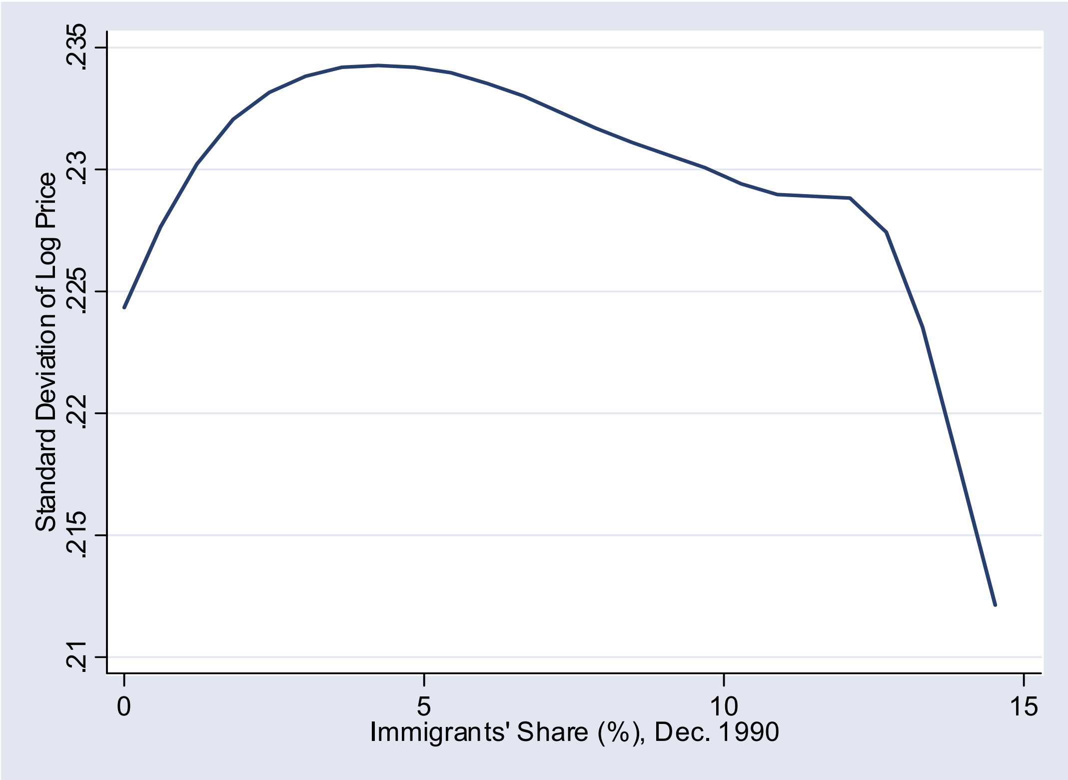

Figure 6: Average Standard Deviation of Log Prices

Table 1. Summary Statistics by City in 1990

	Town	Number of Stores*	Number of Products*	Number of Observations	Total Population**	Immigrant's Share (%)**	Average Price Change (%)****
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1	Afula	3	43	197	27.9	7.9	1.0
2	Akko	11	148	1,345	40.3	6.0	0.5
3	Arad	11	130	841	15.4	8.4	1.0
4	Ashdod	20	139	832	83.9	6.8	0.6
5	Ashqelon	23	214	1,286	59.7	3.7	0.3
6	Bat Yam	41	307	2,787	141.3	5.9	0.9
7	Beer Sheva	47	343	3,354	122.0	7.0	1.3
8	Bene Beraq	20	225	1,979	116.7	2.0	1.2
9	Dimona	4	49	277	26.0	3.5	0.7
10	Giv'atayim	24	252	1,529	46.6	2.6	0.7
11	Hadera	15	150	848	45.6	5.5	0.8
12	Haifa	136	417	8,548	245.9	9.6	0.6
13	Herzeliyya	29	257	2,306	77.2	2.7	0.7
14	Hod Hasharon	5	41	260	26.0	2.7	0.5
15	Holon	44	356	4,043	156.7	4.6	0.9
16	Jerusalem	151	460	9,329	524.5	2.0	1.0
17	Karmiel	5	91	649	24.2	12.4	0.5
18	Kefar Sava	19	186	1,536	61.1	4.4	2.0
19	Lod	11	152	942	43.3	3.0	1.0
20	Migdal Haemeq	7	129	568	17.2	8.7	1.2
21	Nahariyya	12	162	812	34.0	8.5	0.5
22	Nazerat Illit	4	31	205	29.6	14.5	1.1
23	Nes Ziyyona	10	124	713	20.8	4.8	1.0
24	Nesher	4	36	286	11.4	6.1	1.6
25	Netanya	52	387	4,500	132.2	8.2	0.5
26	Or Yehuda	7	82	475	21.9	7.8	0.7
27	Pardes Hanna-Karkur	9	123	595	16.9	2.4	0.8
28	Petah Tiqwa	43	323	4,354	144.0	5.0	0.7
29	Qiryat Atta	10	149	1,159	38.9	5.9	0.9
30	Qiryat Bialik	4	100	846	34.9	6.0	0.6
31	Qiryat Gat	10	169	879	30.0	6.0	1.1
32	Qiryat Motzkin	11	156	824	32.4	6.5	0.7
33	Qiryat Ono	5	29	160	23.1	3.5	1.2
34	Qiryat Shemona	14	122	654	16.6	6.0	0.7
35	Qiryat Yam	10	136	527	35.9	10.0	0.7
36	Ra'anana	14	192	1,148	53.6	3.0	0.3
37	Ramat Gan	50	367	3,814	119.5	3.3	0.3
38	Ramat Hasharon	12	158	832	36.9	0.5	0.6
39	Ramla	11	111	913	47.9	4.8	0.6
40	Rehovot	24	237	1,796	80.3	7.7	0.8
41	Rishon Leziyyon	32	306	2,786	139.5	5.5	1.2
42	Sederot	2	30	98	10.0	2.0	2.1
43	Tel Aviv	248	467	14,692	339.4	4.7	0.6
44	Tiberias	5	40	264	33.4	3.6	0.4
45	Yehud	3	39	254	16.2	3.1	0.3
46	Zefat	7	81	359	19.3	7.3	0.4
47	Araaba	10	74	516	12.1	0.0	1.5
48	Nazerat	27	169	1,195	49.6	0.0	1.4
49	Sachnin	5	20	108	16.3	0.0	0.3
50	Tamra	8	81	445	16.4	0.0	1.1
51	Um el Fachem	4	37	250	25.4	0.0	1.3
52	Shfaraam	7	94	673	20.9	0.0	1.6
	Total	1300	n.r.	90,588	3560.8	4.9***	0.9

Notes: n.r. = not relevant

* Count of stores (products) that appeared at least once during 1990.

** Population in thousands. Immigrant's share in percentages, 31 December 1990.

*** Simple average

**** Price changes based on the longest time difference avaiable for each store-product observation.

Table 2 . Distribution of Store-Product Durations

Duration (months)	Frequency	Percent	Cumulative
1	625	3.8	3.8
2	610	3.7	7.4
3	870	5.2	12.6
4	1,636	9.8	22.5
5	5,898	35.4	57.9
6	619	3.7	61.6
7	935	5.6	67.2
8	4,932	29.6	96.8
9	538	3.2	100.0
Total	16,663		

Notes:
Durations computed for each store-product observation

Table 3 . Immigration and Population Effects at Different Aggregation Levels, Equation (10)

Dep. variable: Long difference in log price

Aggregation level	**City-product-store**		**City-product**		**City**	
	(1)	(2)	(3)	(4)	(5)	(6)
δ (ΔS×100)		**-0.0144**		**-0.0158**		**-0.01852**
product clusters (478)		0.0037**		0.0040**		0.0060**
city clusters (52)		0.0057*		0.0070*		
β (ΔlogL)	**-0.0478**	**1.346**	**0.0022**	**1.425**	**-0.3698**	**1.349**
product clusters (478)	0.1357	0.3737**	0.1567	0.3987**	0.2943	0.6783*
city clusters (52)	0.2506	0.5996*	0.2428	0.6841*		
t_1 and t_0 interacted with $(t_1 - t_0)^{-1}$	√	√	√	√	√	√
Product dummies	√	√	√	√	X	X
R^2	0.101	0.102	0.148	0.151	0.358	0.499
N	16,038	16,038	8,443	8,443	52	52

Notes:

Standard errors in (5) and (6) robust to heteroskedasticity only.

** (*) significantly different from zero at 1% (5%) significance level

Table 4. Immigration and Population Effects from Price Level Equation

Dep. Variable: Log price

Aggregation level: city-product-store

	(1)	(2)	(3)
δ (s×100)		**0.007**	**-0.0128**
product clusters (478)		0.0024**	0.0044**
city×month clusters (559)		0.0014**	0.0046**
β (logL)	**0.0212**	**0.0217**	**1.23**
product clusters (478)	0.0040**	0.0040**	0.4779**
city×month clusters (559)	0.0025**	0.0025**	0.5210*
Month dummies	√	√	√
Product dummies	√	√	√
ProductxMonth	√	√	√
Store dummies	X	X	√
R^2	0.961	0.961	0.971
N	90,588	90,588	90,588

Notes:

The monthly immigrant share is computed as in equation (6) in the text.

The monthly total population level is computed as in equation (7) in the text.

** (*) significantly different from zero at 1% (5%) significance level

Table 5 . Immigration and Population Effects by Product Group- (City-product-store level)

	Dep. variable: Long difference in log price				
	δ (Δs×100)	**s.e.**		**δ (Δs×100)**	**s.e.**
Music	-0.1526*	0.081	Bread	-0.014	0.015
Pork Products	-0.085**	0.040	Preserves	-0.014	0.011
School Supplies	-0.077**	0.033	Kitchen Appliances	-0.012	0.012
Fish	-0.066***	0.023	Dairy Products	-0.012	0.011
Books	-0.065***	0.020	Cakes	-0.011	0.020
Oils & Salads	-0.037*	0.020	Kitchen Products	-0.010	0.035
Cleaning Products	-0.025**	0.011	Cold Cuts	-0.009	0.013
Canned Vegetables	-0.019*	0.011	Frozen Food	-0.008	0.014
Meat Products	-0.015*	0.009	Pictures	-0.008	0.023
Alcoholic Beverages	-0.013*	0.008	Candy,Cookies, etc.	-0.006	0.007
Home	-0.114	0.111	Tea, Coffee, Chocolate Milk	-0.004	0.015
Sport Products	-0.089	0.060	Medicines	-0.001	0.034
Pet food and equipment	-0.078	0.135	Religious Products	0.002	0.028
Baby Products	-0.047	0.043	Cosmetics & Toileterie	0.008	0.020
Car Accessories	-0.023	0.024	Linen	0.011	0.025
Spices (incl. hummus & thina)	-0.021	0.015	Clothes & Accessories	0.015	0.019
Poultry	-0.020	0.011	Electronics Appliances	0.016	0.023
Furniture	-0.014	0.015	Games & Toys	0.025	0.046
F-test for zero Δs×Product group	F(35, 474) = 1.04				
p-value	0.41				
F-test for zero ΔlogPop×Product group	F(35, 474) = 1.05				
p-value	0.39				

Notes:

The estimated regression is as in regression (2) of Table 3 with product group dummies interacted with changes in S and in log Pop.

Entries are the estimated immigration effect for each product (coefficient for reference group + interaction dummy). Standard errors clustered at individual product level (478 products)

*** (**) (*) significantly different from zero at 1% (5%) (10%) significance level

Table 6. Immigration and Population Effects Using Alternative Interpolation Schemes

Dep. variable: Long difference in log price

Aggregation level	**City-product-store**		**City-product**		**City**	
	Constant increment (1)	Aggregate growth rate (2)	Constant increment (3)	Aggregate growth rate (4)	Constant increment (5)	Aggregate growth rate (6)
δ (Δs×100)	**-0.0143**	**-0.0067**	**-0.0156**	**-0.0103**	**-0.01853**	**-0.0142**
product clusters (478)	0.0037**	0.0027*	0.0040**	0.0030**	0.0060**	0.0047**
city clusters (52)	0.0058*	0.0028*	0.0071*	0.0037**		
β (ΔlogL)	**1.332**	**0.542**	**1.4001**	**0.8729**	**1.318**	**1.027**
product clusters (478)	0.3692**	0.2642**	0.3984**	0.3178**	0.6630*	0.6075
city clusters (52)	0.6051*	0.3978	0.6921*	0.4070*		
t_1 and t_0 interacted with $(t_1 - t_0)^{-1}$	√	√	√	√	√	√
Product dummies	√	√	√	√	X	X
R^2	0.102	0.102	0.151	0.151	0.496	0.482
N	16,038	16,038	8,443	8,443	52	52

Notes:
In (1), (3) and (5) interpolation assumes constant monthly increments to the number of immigrants and to total population
In (2), (4) and (6) interpolation assumes that the monthly growth rate in the number of immigrants in each city equals the aggregate monthly growth rate in the whole country.
Standard errors in (5) and (6) robust to heteroskedasticity only.
** (*) significantly different from zero at 1% (5%) significance level

Table 7. Immigration and Population Effects from First-differenced Equation

Dep. variable: First difference in log price

Aggregation level	**City-product-store-month**		**City-product-month**		**City**	
	(1)	(2)	(3)	(4)	(5)	(6)
δ (ΔS×100)		**-0.0163**		**-0.0171**		**-0.0098**
product clusters (478)		0.0032**		0.0035**		0.0039**
city clusters (52)		0.0047**		0.0054**		
β (ΔlogL)	**-0.086**	**1.512**	**-0.099**	**1.52**	**-0.1969**	**0.6782**
product clusters (478)	0.1371	0.3446**	0.1467	0.3653**	0.2592	0.4388
city clusters (52)	0.2541	0.4785**	0.2638	0.4992**		
Month dummies	√	√	√	√	X	X
Product dummies	√	√	√	√	X	X
R^2	0.018	0.019	0.02	0.02	0.012	0.062
N	73,926	73,926	53,619	53,619	52	52

Notes:

Standard errors clustered at 478 products, except in (5) and (6) where they are robust to heteroskedasticity.

** (*) significantly different from zero at 1% (5%) significance level

Table 8. IV Estimates of Immigration and Population Effects

Dep. variable: Long difference in log price

Aggregation level	**City-product store**	**City-product**	**City**
	(1)	(2)	(3)
δ (ΔS×100)	**-0.0163**	**-0.0173**	**-0.0091**
product clusters (478)	0.0092*	0.0078**	0.0095
city clusters (52)	0.0115	0.0096*	
β (ΔlogL)	**1.531**	**1.553**	**0.4731**
product clusters (478)	0.9015*	0.7501**	0.9191
city clusters (52)	1.1157	0.9558*	
t_1 and t_0 interacted with $(t_1 - t_0)^{-1}$	√	√	√
Product dummies	√	√	X
N	16,038	8,443	52

Notes:

The instrumental variable is the share of Russian Immigrants in each city in 1983 (census year)

Standard errors in (3) robust to heteroskedasticity only.

*** (**) (*) significantly different from zero at 1% (5%) (10%) significance level

Table 9 . Immigration and Population Effects with Metropolitan Effects

Dep. variable: Long difference in log price

Aggregation level	**City-product -store** (1)	**City-product** (2)	**City** (3)
δ (ΔS×100)	**-0.0126**	**-0.015**	**-0.019**
product cluster (478)	0.0037**	0.0042**	0.0076*
city cluster (52)	0.0058*	0.0076*	
$\delta^{metro}(\Delta S^{metro}\times 100)$	**-0.003**	**-0.0043**	**-0.0024**
product cluster (478)	0.0041	0.0044	0.009
city cluster (52)	0.0061	0.0073	
β (ΔlogL)	**1.313**	**1.454**	**1.399**
product cluster (478)	0.3753**	0.4168**	0.8315
city cluster (52)	0.6248*	0.7642*	
t_1 and t_0 interacted with $(t_1- t_0)^{-1}$	√	√	√
Product dummies	√	√	X
R^2	0.112	0.152	0.5
N	14,322	7,990	51

Notes:

Sample excludes observations for Jerusalem

Δs^{metro} is the immigration share in metropolitan area of city c not including data for city c

The 4 metro areas are: Jerusalem (1 city), North (17 cities), Center (22 cities) and South (6 cities)

Standard errors in (3) robust to heteroskedasticity only.

**(*) significantly different from zero at 1% (5%) significance level.

Table 10. Time Spent Shopping

(minutes per day)

	Mean	Median	75%	90%	95%	N
FSU Immigrants	25.8	0	45	90	105	187
Natives	15.2	0	15	60	90	4586

Notes:

Data from "Time Use in Israel -Time Budget Survey 1991/92. Shopping defined as everyday shopping and other shopping (not everyday) excluding time spent on personal and medical services.