Heterogeneous Passthrough from TFP to Wages*

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Abstract

What is the impact of firms' productivity shocks on workers' labor earnings? To answer this question, we propose a new method to identify firms' productivity shocks that combines a nonparametric production function estimation method with a set of two-way fixed effect regressions to control for differences in the quality of labor force within a firm. We apply this method on large matched employer-employee data that encompasses the entire population of workers and firms in Denmark. Our dataset allows us to separately study continuing and non-continuing workers, control for workers' endogenous job mobility decisions, and to investigate how the passthrough from firms' shocks to wages varies across narrow population groups. We find an elasticity of workers' hourly wages to firms' productivity of 0.08. This implies that a change of one standard deviation in firm-level TFP generates a change of $1,100 US dollars in annual wages for the average worker in Denmark. We also find that both persistent and transitory shocks to firms are passed on to workers' wages and that there is a marked asymmetry between positive and negative productivity shocks. In fact, after controlling for selection, the elasticity of hourly wages to a negative productivity shock is twice that of a positive productivity shock of the same magnitude. This suggests that workers are more exposed to negative than to positive shocks to firms. Furthermore, we find that the changes in wages due to variation in firm productivity are quite persistent and do not dissipate even 5 years after the shock. By looking at the heterogeneity of passthrough within firms and workers groups we provide insights about the mechanisms that could explain the asymmetric passthrough from firms' shocks to wages we observe in the data.

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1 Introduction

How do fluctuations in firms' idiosyncratic productivity affect workers' wages? How does this vary over time and across firms and workers of different characteristics? The answers to these questions are important as they can help us to understand how firms differ in their ability to set wages, why workers of similar characteristics receive different salaries across firms, and what is the role of firms' shocks in determining worker income instability. At the core of these questions is the idea that some of the gains and losses in firms' productivity are passed on to their workers.

In this paper, we use administrative matched employer-employee panel data covering the entire private sector of Denmark to provide new evidence on the passthrough from firms' idiosyncratic *productivity* shocks to worker's wages. Our main object of interest is the elasticity of workers' hourly wages with respect to firms' productivity shocks. The richness of our dataset allows us to address some of the challenges faced by the existing literature. These challenges are two-fold. The first is to identify plausibly exogenous fluctuations in firm productivity. Most papers use variations in value-added or sales as proxies for shocks to firm productivity. Fluctuations in these variables, however, might not reflect exogenous shocks but rather endogenous decisions by the firm. In this paper, we instead leverage the rich firm- and worker-level information available in our dataset to estimate Total Factor Productivity (TFP) at the firm-level using a dynamic structural model.

To estimate firms' TFP, we build on the nonparametric estimation approach proposed by Gandhi, Navarro and Rivers (2018)–hereafter GNR. We deviate from the approach proposed by these authors in that we use our rich individual-level data to control for differences in the quality of labor employed within each firm. Each firm's labor input is calculated as the contribution of its workers' observed and unobserved characteristics estimated from a series of two-way fixed effect wage regressions as in Abowd, Kramarz and Margolis (1999)–hereafter AKM. We also deviate from the standard AKM wage model in that we allow the firm fixed effects to vary across time in the wage equation, effectively allowing changes in firms' characteristics and productivity to have a dynamic impact on workers' wages. Furthermore, our estimation approach allows us not only to identify plausibly exogenous variation in firms' TFP, but also to separate shocks in terms of their sign (positive versus negative) and duration (transitory versus persistent). As we shall see, productivity shocks of different characteristics have a differential impact on

workers' wages.

The second challenge is to identify which workers are affected by firms' shocks. In general, the literature has focused on incumbent workers who remain at the firm after a shock ("stayers"). This may lead to biased estimates of passthrough if, for example, workers tend to quit their jobs rather than suffer a large wage decline resulting from a negative firm shock. Since one can only estimate *within-firm* passthrough for workers who select into staying at the firm, estimated passthrough will be biased towards zero, overstating the degree of insurance provided by the firm. In this paper, we address this (selection) bias in two ways. First, we control for the endogenous separation decision of the worker by exploiting independent variation derived from workers' spousal linkages. In particular, we predict each worker's probability of staying at a firm as a function of her and her employer's characteristics, as well as her marital status, the observable characteristics of her spouse and the spouse's employer (if employed) including shocks to her spouse's employer. The underlying assumption is that a worker's marital status, spouse's characteristics, and shocks to their spouse's firm will affect that worker's job mobility decisions, but not the elasticity of wages to productivity in their own firm.

To further study the impact of firms shocks on those who transition between jobs ("switchers"), we evaluate how differences in firm productivity impact their wages by directly following workers across different employers and comparing shocks affecting these firms and their productivity level. Since these estimates are subject to the same selection problem as the estimates of within-firm passthrough, we employ a similar strategy to correct for bias in cross-firm passthrough. To the best of our knowledge, ours is the first paper to leverage data-based exclusion restrictions to directly address selection bias when evaluating the passthrough from firms' shocks to workers' wages. Correcting for selection turns out to be quite important, especially when studying the passthrough of negative productivity shocks.[1]

As a preliminary illustration of our main results, Figure 1 shows the relation between firms' TFP growth and workers' wages. To construct this figure, we first partition our sample of firms into 41 equally-sized bins based on their TFP growth–measured as the change in log TFP between periods t and $t-1$–with the corresponding density plotted

[1]The selection bias problem is commonly recognized in the passthrough estimation literature. A few papers (e.g. Friedrich, Laun, Meghir and Pisteferri (2019)) have attempted to address the problem using two-step procedures similar to our approach. These papers generally rely on functional form assumptions on the stochastic process of firm outcomes and worker earnings.

in the left axis. Then, within each bin, we calculate two measures of wage growth: the change in workers' log hourly wages (plotted as dots on the right axis) and the residual change in workers' hourly wages after we have controlled for firm and worker observable characteristics and for selection (plotted as squares on the right axis also).[2] Two salient features of this figure are worth noticing. First, the distribution of firms' TFP growth is quite disperse with a substantial share of firms experiencing changes in productivity of more than 30% in a given year. Second, log hourly wages do vary with firms' productivity growth, especially when the firm experiences positive growth, but they appear to be insulated from negative productivity changes. In fact, the average hourly wage growth is positive across the entire TFP growth distribution (all dots are above the zero line plotted on the right axis), suggesting that (raw) hourly wages are subject to downward rigidity. Hence, a simple inspection of Figure 1 would indicate that, although there is some passthrough from productivity to wages, this is small and mostly due to positive shocks to productivity. This conclusion, however, ignores the fact that firms with different TFP growth differ in several dimensions, including labor quality, and more importantly, that those workers who stay in the firm after a negative productivity shock are a selective sample. When we control for the endogenous worker mobility the picture changes substantially. In particular, we find a significant increase in the slope of the average wage growth coming from the left tail of the TFP growth distribution–compare the dots with the squares in Figure 1. Hence, controlling for selection reveals a substantial increase in the elasticity of workers' wages with respect to fluctuations in productivity.[3]

The rest of the paper delves into the details of the relationship between firms' productivity shocks and workers' wages. Our main empirical analysis comprises a series of worker-level panel regressions that relate the change in individual hourly wages for stayers–i.e. workers who remain employed in the same firm–with different measures of

[2]Section 3 explains our TFP estimation and selection correction procedures in detail.

[3]Adjusting for selection impacts the entire distribution of hourly wage growth. As we show in the Figure A.1 in the Appendix, not controlling for selection would led to conclude that the median worker in firms experiencing a decline in productivity of 30% would have seen almost no change in their hourly wages, while workers in the 90th percentile of the hourly wage distribution experience an increase of 6%. Instead, after we have controlled for selection, the median worker experiences a decline in hourly wages of 2.5%. For the workers in the 90th percentile instead, the increase in wages is around 3%. Interestedly, the cross-sectional dispersion of hourly wage growth (measured by the 90th-to-10th percentiles differential) is relatively constant across the firms' TFP growth distribution. Note that, To avoid the disclosure of any sensitive information, we report the mean of the observations *within* a percentile-band rather than the individual observation at the percentile cutoff.

firm productivity shocks. Using these regressions, and consistent with the results shown in Figure 1, we find an elasticity of hourly wages to a change in TFP of 0.08 which is economically and statistically significant. Quantitatively, this means that, on average, an individual who works full-time at a firm that experiences a one standard deviation increase in TFP receives an increase in annual earnings of $1,075 US dollars, or around 1.8% of the average Danish annual salary. Considering that in a typical year around a 20 percent of the firms in our sample (which employ around 25% of all the workers in the Denmark) experience a change in productivity of at least one standard deviation away from the mean (the standard deviation of firm TFP growth is equal to 0.23 in our sample), we conclude that fluctuations in firm productivity can have important aggregate implications for workers' wages.

We then study whether negative and positive changes in firms' productivity have a differential impact on workers' wages. Standard bargaining models predict that for stayers, positive productivity shocks should command a higher passthrough than negative ones as the latter would move the surplus of the match closer to the point at which the match is destroyed. Hence, on average, bargaining models would predict higher passthrough from positive shocks than from negative shocks. Our results, however, indicate just the opposite. In fact, we find that the elasticity of workers' wages to negative productivity growth is almost twice as large as the elasticity to a positive change in productivity.[4] Our calculations indicate that for the average worker, an increase in productivity of one standard deviation generates an increase in annual earnings of $840 US dollars, whereas a decrease in productivity of the same magnitude generates a drop in annual earnings of $1,580 US dollars.

We then examine how workers' wages respond to persistent and transitory shocks to firm productivity. With the exception of few papers (see for instance Howell and Brown (2019)), the broad consensus in the literature is that workers' wages respond to persistent changes in firm productivity but do not react to transitory shocks.[5] Our results are consistent with the existing evidence that persistent shocks to firms have a higher passthrough than transitory shocks; However we do find that both types of shocks

[4]Contract theory also provides insights about the transmission of firms' idiosyncratic productivity shocks to workers' wages. For instance, models with firm commitment as in Harris and Holmstrom (1982) would predict that positive shocks are passed to the wages of stayers while negative shocks are not. Models with imperfect monitoring instead (e.g. Lamadon (2016)), predict positive passthrough of both, positive and negative shocks, but this passthrough is symmetric.

[5]See Card, Cardoso, Heining and Kline (2018); Guiso and Pistaferri (2020) for recents reviews of the literature.

are statistically and economically significant. Furthermore, by comparing hourly wage changes at different horizons, we show that persistent shocks to firms' productivity have an almost permanent impact on worker's hourly wages. In contrast, although transitory shocks to productivity do have a significant immediate impact on wages, this impact dissipates almost completely three years after the shock.

As we suggested earlier, selection plays an important role in shaping the impact of firms' shocks on workers' wages. Hence, in order to evaluate the extent of the bias generated by selection we provide a set of results in which we do not control for the endogenous selection of workers. By doing this we reach two conclusions. First, selection biases the passthrough coefficient towards zero for both positive and negative shocks, reducing the overall impact of productivity shocks on wages, and second, that this bias is more important for negative than for positive shocks. In fact, if we were to ignore selection, we would conclude that the wage elasticity to positive shocks is almost twice the elasticity to negative shocks, which is the opposite of what we find in our baseline selection-corrected results.

The richness of our dataset allows us to study several degrees of heterogeneity, which help us shed light on the different channels that might explain why labor earning fluctuations might be linked to changes in firms' idiosyncratic productivity. Overall, we find that passthrough varies considerably across firms and workers of different types. For instance, we find that the passthrough for high wage workers–those at the top quintile of the income distribution–is significantly higher than for low-wage workers–those at the first quintile of the income distribution. Perhaps surprisingly, we also find that high wage workers are more exposed to persistent TFP shocks than low wage workers, especially for persistent negative shocks. We find similar patterns if we rank workers by their quality–as measured by our AKM estimates. Consequently, we conclude that positive shocks to firms increase income inequality while negative productivity shocks reduce it.

Older workers benefit more from persistent positive shocks and suffer less from negative shocks than younger workers. We also find that negative passthrough is hump-shaped in tenure, with recently hired workers–less than 2 years of tenure–and tenured workers–those with 15 years of more of tenure–being less exposed to negative shocks than mid-tenure workers. Transitory shocks display much less heterogeneity in passthrough than persistent shocks across all of these measures.

We also find significant passthrough for workers switching between firms. Overall,

workers who experience wage gains have moved into more productive firms, with larger gains in wages associated with greater moves up the productivity distribution. Interestingly, larger wage gains are associated with greater moves up the productivity ladder not because of moves into increasingly productive firms, but due to moves out of decreasingly productive firms. Quantitatively, workers that experience an increase in hourly log wages of 10 log points have moved, on average, to a firm with 15 log points higher productivity. A 50 log point gain, on the other hand, is associated with a move to a 40 log point more productive firm. However, both of these sets of workers move into firms of roughly the same productivity. The workers gaining 50 log points in wages are moving out of firms with 25 log points lower productivity than those gaining 10 log points in wages. Small decreases in hourly wage are actually associated with small increases in average firm productivity, while larger decreases in hourly wage are linked to decreases in average productivity. Workers also tend to switch into firms with higher productivity growth. In fact, the average switcher in every percentile of the wage growth distribution is moving out of a firm with negative productivity growth and into one with positive productivity growth. Although we find that the average passthrough elasticityis smaller for switchers than for stayers, the economic impact is twice as large (about $2,166 US dollars on average) since between-firm productivity differences tend to be much larger than within-firm productivity changes.

On the firm side, we find that high productivity firms have lower passthrough than low productivity firms, as do firms with higher labor market power (measured as by employment share of a particular firm within a local labor market).

Finally, we show that the passthrough of persistent productivity shocks is state-dependent, changing substantially over the business cycle. During an expansion, we find elasticities that are in line with our baseline results that both positive and negative shocks are significantly passed on to workers' wages. During a recession, however, the passthrough from positive productivity shocks collapses–becoming almost zero for persistent shocks–whereas the passthrough from negative shocks remains almost unaltered. In other words, our results suggest that recessions are not periods in which firms are unable to cut wages when facing an idiosyncratic negative shock–because of union pressure for instance–but rather they are unwilling to increase wages when facing a positive idiosyncratic shock.

Related Literature. Our paper relates to several strands of the literature. First and foremost, we relate to the rent-sharing literature that studies the relationship between firm shocks and worker earnings. In their seminal contribution, Guiso, Pistaferri and Schivardi (2005) study the passthrough from firms value added shocks to wages and the degree of insurance provided by firms using matched employee-employer data from Italy. They find a passthrough coefficient of 0.07 from permanent shocks and almost no passthrough from transitory shocks to firms. Their methodology has been replicated for several countries, included the United States, delivering surprisingly similar results.[6] We differentiate from this paper–and the subsequent literature–in at least three important aspects. First, we measure productivity shocks using a dynamic structural model of firm production; Second, by using hourly wages we are able to isolate the impact of firms productivity on workers' wage rate from adjustment in the number of hours an individual works in a year; And third, we control for the endogenous selection of workers. Interestingly, we find an average passthrough coefficient that is well in line with other estimates in the literature. By separating positive from negative shocks, however, we find substantial asymmetry in passthrough.

More recently, several authors have used quasi-experiments to tease out shocks to firms and how these are passed to workers' wages. For instance, Kline *et al.* (2019) studies the rent sharing among innovative firms that receive a patent approval. Similarly, Howell and Brown (2019) use cash flows received by firms from government grants as a measure of shocks. These papers focus on a very particular–yet important–set of young and small firms, which might not be representative of the entire economy.

Our paper also relates to the literature that analyzes the extent of downward wage rigidity. Several recent papers have studied the presence of wage rigidity using administrative data (see for instance Kurmann and McEntarfer (2019), Grigsby *et al.* (2019), and Elsby and Solon (2019)). Our results suggest at least part of the downward wage rigidity found in the data is partially driven by selection as workers that stay in a firm after a negative shock to the firm are precisely those for whom wages do not change.

The method we use to estimate firms' productivity is similar to those proposed by Hellerstein and Neumark (2007), Fox and Smeets (2011), and more recently, Bagger *et al.*

[6]Several recent papers study the relation between firm's shocks and worker's wages. See for instance, Friedrich *et al.* (2019),Carlsson *et al.* (2015), Garin *et al.* (2018), Guertzgen (2014), Lamadon *et al.* (2017),Rute Cardoso and Portela (2009),Barth, Bryson, Davis and Freeman (2016), Lamadon (2016), Juhn, McCue, Monti and Pierce (2018) among others. See Manning (2011), Card *et al.* (2018), and Guiso and Pistaferri (2020) for recent surveys.

(2014) and Bagger and Lentz (2019) who also incorporate worker-level characteristics in order to better control for differences in labor quality across firms. In a more closely related paper, Lochner and Schulz (2020) also merges the AKM approach to measure labor quality with a production function estimation method similar to what we use in this paper. We differentiate from these studies in that we consider a richer set of workers' characteristics in our AKM estimation, and more importantly, that we allow for passthrough in our AKM model by allowing the firm effect to vary with time.

The rest of the paper proceeds as follows. In Section 2, we introduce our data sources and discuss our sample selection. Then, in Section 3, we present our estimation strategy. Section 4 discusses the main results of our analysis. Section 5 studies how the passthrough from firms' shocks to workers' wages varies across firms and workers of different characteristics. Section 6 concludes.

2 Data

Our main source of information is a matched employer-employee administrative dataset from Statistics Denmark covering the years 1995 to 2010. We obtain worker-level information from the Integrated Database for Labor Market Research which is an annual database containing employment and personal/demographic information for the entire population of Denmark. From this dataset, we obtain several key variables such as annual income and hourly wages for each job at which an individual worked during the year, total number of hours and days worked in each job, occupation, labor market status, position within the firm, age, gender, education, and tenure within the firm. Our data also contains an identifier that links each individual with his or her spouse. This information will be crucial when estimating the first-stage of the selection model we use in Section 3.3 to correct for bias in the passthrough regressions. For our baseline results, we consider the change in log average hourly earnings as the main outcome variable at the individual level. Hourly wages are calculated as the ratio between the annual labor earnings of a worker and the total number of hours worked within a year. In this way, we are able to isolate the impact of a shock to firms' productivity on workers' average wage rate. Importantly, since firms can also respond to shocks by changing the number of hours their employees work, we also study the impact of firms' shocks on the change in workers' hours and annual earnings separately.

In our baseline sample, we consider workers who are 15 years and older, and who are

not working in the public sector or are self-employed. We use this sample to estimate the AKM and production models described in Sections 3.1 and 3.2. For our main regression estimates, however, we focus in a subset of full-time workers (defined as individuals that worked more than 35 hours within a year) and whose annualized total labor earnings are above 30,000 danish krone (about 4,600 US dollars of 2010). Despite these restrictions, our estimates are based on a large dataset of 8.98 million worker-year observations. Panel A of Table I provides basic summary statistics of our worker-level sample for selected years. Our sample of workers (around 0.5 million workers per year) is 30% female, consists largely of workers with at least some post-secondary education (65% of the sample), and workers between 25 and 55 years old (around 80% of the sample), with an average annual income of $53,103 US dollars in 2010.

We match this individual-level panel to a firm-level panel–the Firm Statistics Register–which contains annual accounting and input use data for the universe of Danish private-sector firms.[7] The key firm-level variables we use are annual revenue, value added, capital stock, intermediate expenditure, and employment (in full-time equivalents), as well as firm age, location, and industry. This data allows us to construct robust measures of TFP following the methods developed by Levinsohn and Petrin (2003), Ackerberg *et al.* (2015), Gandhi *et al.* (2018), and others. We discard firms with invalid or imputed measures of sales, employment, and other key variables.[8] Panel B of Table I shows few sample statistics for selected years. Our effective sample (defined as firms which contain individuals in the above worker sample) contains around 45 thousand firms per year (for a total of 0.6 million across all years), most of which have been in operation for at least 10 years (67.6%). These old, well established firms represent around 60% of the employment in our sample. As in other countries, the employment size distribution is highly skewed, with a small group of firms with 100 or more employees (3% of firms) accounting for a disproportionate share of total employment in the economy (45% of employees).

[7]The register begins with the manufacturing sector in 1995, and gradually adds in the remaining sectors, with universal coverage of the Danish economy from 2001 on. Our results do not change if we consider data from 2001 on.

[8]Our TFP estimation procedure requires data from years $t-1$ and $t-2$ in order to recover productivity in year t. Thus, our final summary stats and estimation sample consists of firms of age 3 and greater, since we do not observe productivity for younger firms.

3 Empirical Strategy

In this section, we discuss our empirical strategy which consists of three parts. First, we study a statistical model of earnings which we use to separate the contribution of worker and firm characteristics in determining individual hourly wages (Section 3.1). We then discuss our TFP estimation method where we use the results from our statistical model of wages to control for unobserved variation in the quality of the labor inputs employed by the firms (Section 3.2). Finally, we discuss how we correct for the selection bias which arises from endogenous worker mobility in our estimates of the impact of firm-level productivity shocks on wages (Section 3.3).

3.1 Two-way Fixed Effect Model of Wages

To measure workers' ability separately from the characteristics and wage-setting policies of the firms where they work, we use a modified version of the additive worker-and-firm fixed effect model proposed by AKM. In particular, we assume that the log hourly wage w_{ijt} for individual i working in firm j in period t is given by

$$w_{ijt} = \underbrace{\alpha_i + \Gamma' X_{it}}_{\text{Ability Units}} \quad + \quad \underbrace{\psi_{j(i,t)t} + \xi_{ijt}}_{\text{Per-unit Ability Price}} \quad , \tag{1}$$

where α_i is an individual fixed effect, $X_{i,t}$ is a set of worker observables, $\psi_{j(i,t)t}$ is a firm-by-time fixed effect that identifies the firm j in which worker i is employed in period t, and ξ_{ijt} is a residual that captures all the different forces that can affect workers' wages but are unrelated to individual or time-varying firm characteristics.[9]In this way, we are able to separately identify the component of hourly wages that is due to the characteristics of the worker–which we refer to as ability units–from the component of hourly wages that is due to differences across firms and time–which we refer to as the time-varying per-unit ability price paid by the firm.

Our specification differs from the standard two-way fixed effects regression used in the literature in several crucial ways. First, because of data limitations, most papers use annual labor earnings as the dependent variable, which might confound variations in the

[9]Our identification relies on the assumption, similar to AKM, that labor mobility is not correlated with ξ_{ijt}. However, our assumptions are weaker than the AKM assumption, as we do allow workers to switch firms in response to shifts in $\psi_{j(i,t)t}$, thereby allowing passthrough from firm productivity to wages to play a role in worker mobility decisions.

wage rate received by a worker and the number of hours worked by an individual during the year. This may be particularly relevant for workers with low labor market attachment or those transitioning between jobs. For this reason, researchers have opted to discard workers with labor earnings below a certain minimum threshold.[10] Our dataset contains detailed information on hours worked and hourly wages for each individual-firm pair during a year allowing us to use average hourly wages as the main dependent variable.

Second, we do not assume that the contribution of firm characteristics to workers' wages is fixed, as in the standard AKM case, but rather time-varying, as indicated by the time subscript on $\psi_{j(i,t)t}$. This allows workers to respond to firm-level shocks by moving across firms, and is consistent with the idea that firms' idiosyncratic productivity shocks or other changes in firms' characteristics may influence workers' wages.

Assuming time-by-firm fixed effects, however, imposes additional restrictions on the construction of the connected set that allows us to estimate the large set of fixed effects in equation (1).[11] As in the standard AKM method, worker and firm-time fixed effects can only be identified within a connected set of firms that are linked through employment transitions. In order to estimate the time-by-year fixed effects in equation (1), we use information on all of the firms in which an individual has worked during a given year, along with the corresponding wages and hours. Hence, in our dataset, an individual can appear in different firms within the same year working at different hourly wages. Multiple worker-year observations increase the number of between-firm connections, the number of individual-level observations for each worker, and the size of the connected set. Importantly, holding multiple jobs in one particular year is quite common among workers in our sample: We find that 54.4% of workers have held a second job while 4.7% of workers have held a third job during a year. In our sample, we consider a worker's top three jobs in a given year (defined by total hours worked that year). Obtaining estimates of the individual contributions to wages for every employment connection in the economy also allows us to avoid bias or measurement issues when we aggregate our

[10] Typically, this minimum threshold depends is set to a proportion of the total amount of income that a person would earn working at the minimum wage during a fraction of the year (Song *et al.*, 2019).

[11] Few other papers have allowed for time-varying coefficients in AKM regressions. For instance, Bagger *et al.* (2014) allows for occupation-firm fixed effects that vary with time and Bagger and Lentz (2019) incorporates time-varying firm-level observables into their estimation. Card *et al.* (2013) estimate a similar model where instead of firm-time fixed effects, they estimate firm-worker match effects using a similar identification strategy. None of these papers allow for firm-by-time fixed effects which we see as crucial when thinking about the dynamic impact of firms on worker income, such as estimating the passthrough from TFP shocks to wages.

individual effects up to our firm-level ability-adjusted measures of labor inputs in section 3.2. Since our dependent variable is the log of hourly wages, to estimate the coefficients in Equation (1), we include all workers–full time and part time–in all their jobs. This is important for the estimation of firm-level TFP: if were to restrict our analysis to only full-time workers, or only a worker's primary job, we would be undercounting labor inputs for firms which use a higher proportion of part-time workers (which may vary by productivity, biasing our estimates).

Figure 2 gives an illustration of how identification works in our model with firm-time fixed effects and multiple observations per worker-year. The left panel shows a theoretical set of jobs across two years for three different workers (represented by solid purple, dotted red and, dashed green lines). In this example, worker 1 has three jobs in period 1, working at firms A, B, and C. In period 2, worker 1 has two jobs–working at firm A and B. Because we estimate firm effects separately for each year, we treat each firm-year observation as a separate firm. Thus A1 and A2 refer to firm A in two different periods. The middle panel shows the network graph of all 5 firm-year nodes if we were to only consider each worker's first or primary job (as is typically done in the literature). For example, worker 1 moves from A1 in period 1 to A2 in period 2, while worker 3 moves from C1 to B2. The result is two (disjoint) connected sets, the first with firms A1 and A2, and the second (largest connect set) with firms B1, B2 and C1. Each firm is connected to the rest of their set with just a single worker transition.

The right-most panel of Figure 2 shows the network graph when we consider all of the available worker job information. In this setting, each first-period job worked by an individual is connected to every second-period job worked by that same individual, leading to a connected set including all 5 firms. Moreover, each firm in this larger connected set is connected by at least 3 worker transitions to the rest of the set, strengthening identification of the firm and worker fixed effects. The largest connected set that we use to estimate the model in equation (1) includes 94% of the firms and 99% of all the workers in our original sample.[12]

We then estimate the model in equation (1) using this largest connected set of firms. To estimate the model we pool all of our worker data from 1991 to 2010, providing us with a robust measure of our individual fixed effects and allowing us to compare the levels of firm effects over time without making further normalization assumptions. In our

[12]If we restrict our sample to only include an individual's most important employment connection (by total income), the largest connected set decreases in size, covering only 89% of firms.

regressions, we include a rich set of worker level observables including age, occupation, education, position within the firm, labor market experience, and tenure within the firm, most of which are typically absent in other administrative datasets. We allow the effect of education, occupation and worker position to vary with time, which allows us to capture both the effects of time changing observable individual characteristics and aggregate trends such as skill-biased technical change and outsourcing. For example, we allow the return to college or individual occupations to increase or decrease flexibly over time. Including a thorough set of controls helps us to tease out as many factors as possible that may potentially confound our estimates when we want to separately identify the worker's versus firm's contribution to wage levels.

Identifying the fixed effects in our model requires some modifications of the standard AKM case. First, since our firm-side unit of observation is a firm-time pair, rather than just a firm, every worker in the economy is considered a "switcher" even if they stay in the same firm between two periods. The firm-time effect is thus identified from changes in mean firm wages across firm-time pairs. In models with invariant firm fixed-effects, one can identify the returns to observed worker covariates using cross-time wage variation for workers who stay at a firm in two consecutive periods (stayers): $(i, j, t-1) \rightarrow (i, j, t)$,

$$\begin{aligned} w_{ijt} - w_{ijt-1'} &= \alpha_i + \psi_{j(i,t)} + \Gamma' X_{it} + \xi_{ijt} - (\alpha_i + \psi_{j(i,t)} + \Gamma' X_{it-1} + \xi_{ijt-1}) \\ &= \Gamma'(X_{it} - X_{it-1}) + \xi_{ijt} - \xi_{ijt-1} \end{aligned} \tag{2}$$

By including time-varying firm effects one is basically assuming there are no stayers, so our identification of the returns to worker covariates instead relies on "common switchers", or workers who make the same switch between firms across two different periods. This can include those who would have been counted as stayers in a standard AKM setup, but also workers who transition between different firms together (though this is much less common). To illustrate this, consider two workers i and m who work in firm j in period $t-1$ and firm k in period t. This gives us

$$\begin{aligned} w_{ikt} - w_{ijt-1} &= \alpha_i + \psi_{k(i,t)t} + \Gamma' X_{it} + \xi_{ikt} - [\alpha_i + \psi_{j(i,t-1)t-1} + \Gamma' X_{it-1} + \xi_{ijt-1}] \\ &= (\psi_{k(i,t)t} - \psi_{j(i,t-1)t-1}) + \Gamma'(X_{it} - X_{it-1}) + (\xi_{ikt} - \xi_{ijt-1}), \end{aligned}$$

and

$$\begin{aligned} w_{mkt} - w_{mjt-1} &= \alpha_m + \psi_{k(i,t)t} + \Gamma' X_{mt} + \xi_{mkt} - [\alpha_m + \psi_{j(i,t-1)t-1} + \Gamma' X_{mt-1} + \xi_{mjt-1}] \\ &= (\psi_{k(i,t)t} - \psi_{j(i,t-1)t-1}) + \Gamma'(X_{mt} - X_{mt-1}) + (\xi_{mkt} - \xi_{mjt-1}), \end{aligned}$$

which implies

$$\Delta w_{it} - \Delta w_{mt} = \Gamma'(\Delta X_{it} - \Delta X_{mt}) + (\Delta \xi_{it} - \Delta \xi_{mt})$$

Since in our sample a large number of workers are "common switchers", we are able to recover Γ. The rest of the identification intuition follows directly from AKM.

Once we have estimated the model in equation (1), we can decompose the variance of log hourly wages as follows,

$$Var\left(w_{ijt}\right) = \underbrace{Var\left(\alpha_i + \Gamma' X_{it}\right)}_{\text{Worker Component}} + \underbrace{Var\left(\psi_{j(i,t)t}\right)}_{\text{Firm Component}} + \underbrace{2 \times Cov\left(\alpha_i + \Gamma' X_{it}, \psi_{j(i,t)t}\right)}_{\text{Wage Sorting Component}} + \underbrace{Var\left(\xi_{ijt}\right)}_{\text{Residual}}, \quad (3)$$

where the first and second components capture the fraction of the variance of log hourly wages accounted for by heterogeneity across workers and firms, respectively. The third component accounts for the variation in log earnings that can be attributed to the sorting of workers to firms in terms of their wages, that is, how much of the variation in wages is due to the fact that high quality workers–as measured by $\alpha_i + \Gamma' X_{it}$–are hired by high-wage firms–as measured by $\psi_{j(i,t)t}$.

Table II presents the basic statistics from our AKM estimation for two separate periods and for the pooled sample across all years available in our data. We find that around 50% of the variance of log hourly wages is accounted for by workers' characteristics and 11% is accounted for by firm-by-time effects. Our estimates also show that sorting does not account for much of the variation in hourly wages (1%).[13] Our estimates are

[13] In a companion paper (Chan *et al.*, 2019b) using the same method, we find strong sorting between workers' fixed effects and firm *productivity*. That is, although high quality workers might not seem to work in high pay firms–as measured by the correlation between the worker fixed effects and firm fixed effect–we find that high quality workers do work in high productivity firms–as measured by the

similar to other studies that also implement the AKM estimator that typically find that workers' characteristics accounts for at least 60% of the total dispersion in labor earnings (as in Lamadon *et al.* (2019) and Sorkin (2018)) whereas firms' characteristics account for around 10% of the variation in labor income (as in Lamadon *et al.* (2019) and Song *et al.* (2019)).

One important concern about of our setting–which is common to all AKM-style fixed effect estimations–is that there are many firm-time pairs that are weakly connected to the largest connected set. For example, in our dataset we find that roughly 5.2% of all firm-time observations have only one mover connecting these firms to the largest connected set, with another 13.3% of firm-time observations having only two connections. These weak connections may bias our estimates. As pointed out by Andrews *et al.* (2008), if firm fixed effects are identified using a small number of workers that move across firms, the AKM estimates will be biased, overstating the role of firms relative to the role of sorting in accounting for the variation in labor earnings. Notice, however, that using multiple job observations for workers helps to reduce such limited mobility bias: If we only include one job per worker, we find that 7.0% of firm-time observations have only one link (rather than 5.2% in our baseline sample) and 20.1% only have two links to the largest connected set (versus 13.3% using workers' top three job connections). Furthermore, the limited mobility bias only affects our inference about the importance of firms and sorting in accounting for income inequality, but not the estimation of the importance of worker heterogeneity, which is crucial for the method we use to estimate firms' TFP. We perform a series of robustness exercises on this data using this method in Chan *et al.* (2019b) and conclude that limited mobility bias is not an important factor in our AKM estimates.

3.2 TFP Estimation

One of the main challenges in studying the passthrough from firms' shocks to workers' wages is to find exogenous sources of variation in firms' outcomes. The literature has relied on several measures such as variation in value-added (Guiso *et al.*, 2005), export demand shocks (Garin *et al.*, 2018), or patent/grant applications (Kline *et al.*, 2019; Howell and Brown, 2019). In this paper, we estimate (revenue) TFP shocks using a dynamic structural model of firm production. In particular, we build on the flexible approach proposed by Gandhi *et al.* (2018) by allowing labor inputs to adjust dynamically

correlation between the worker fixed effects and firm TPF.

in response to productivity shocks, and by correcting for unobserved variation in labor input quality using the estimates from the fixed effect model described in section 3.1. In order to conserve space, here we provide a general overview of our estimation procedure. In a companion paper (Chan *et al.*, 2019b) we provide further details of this approach and show how controlling for labor quality impacts the shape and dynamics of the firm TFP distribution.

There are several problems we need to address when identifying our firm shocks. First, we want to identify exogenous shocks to firm productivity separately from endogenous shifts in inputs. This is important since wages may be correlated with changes in capital stock or employment as well as changes in productivity, and difficult because firms also adjust the capital stock, employment, and other inputs in response to those same exogenous productivity shocks.[14] We are interested in how unanticipated shocks to the firm are passed on to wages, rather than how planned endogenous changes in input mix affect (or are driven by) wages. Second, we need to ensure that our estimation method is consistent with the analysis in the rest of the paper. In particular, we need to recover TFP without relying on the assumption that labor markets are perfectly competitive or that firms are price takers in labor markets, as both directly preclude the possibility of passthrough from idiosyncratic productivity shocks to wages. We also cannot assume that labor is a "predetermined" input like capital, since our empirical analysis hinges on the observation that labor inputs do adjust in response to contemporaneous productivity shocks.

With these considerations in hand, our approach begins with a standard representation of a firm-level gross production function in levels,

$$Y_{jt} = F\left(K_{jt}, L_{jt}, M_{jt}\right) \exp\left(\nu_{jt}\right), \tag{4}$$

or in logs,

$$y_{jt} = f\left(k_{jt}, \ell_{jt}, m_{jt}\right) + \nu_{j,t}, \tag{5}$$

where ν_{jt} is the Hicks-neutral total factor productivity of firm j in period t. We also

[14] This is the *transmission* bias problem which has been a central concern of the TFP estimation literature going back to Marschak and Andrews (1944).

assume that ν_{jt} is given by

$$\nu_{jt} \quad = \quad \omega_{jt} + \epsilon_{jt},$$

where ω_{jt} is the persistent component of firm productivity which is assumed to be first-order Markov and given by $\omega_{jt} = \mathbb{E}[\omega_{j,t}|\omega_{jt-1}] + \eta_{j,t}$, where η_{jt} is a shock to the *persistent* component of firm's productivity and where ϵ_{jt} is an i.i.d. ex-post *transitory* shock which is uncorrelated with adjustments in inputs. In what follows we use the terms *persistent shock* and *transitory shock* to refer to η_{jt} and ϵ_{jt} respectively. To identify these shocks, we impose standard assumptions on the timing and information sets of the firm's input and production decisions which allow us to separately identify η_{jt} and ϵ_{jt}.[15]

The goal of estimating TFP rather than using value added is to separate ν_{jt} from the adjustments on capital, K_{jt}, labor, L_{jt}, and materials, M_{jt}. As it is standard in the literature, we measure Y_{jt} as real revenues, K_{jt} as the real value of the capital stock (using the perpetual inventory method), and M_{jt} with the real value of intermediate input expenditures.[16]As for the labor input, L_{jt}, several alternatives have been proposed in the literature to measure the labor input demanded by the firm . The most common choices are to use the total number of employees working for firm j in year t or the total number of hours worked by those employees. This is a problem, as cross-sectional differences in the quality or composition of workers across firms will be loaded into ν_{jt}. Similarly, changes in the quality of a particular firm's workforce over time, possibly driven by productivity shocks, will also be interpreted as changes in $\nu_{j,t}$. For example, if a firm replaces a full-time janitor with a full-time manager to better organize the

[15]Following GNR, we assume that capital $K_{j,t}$ is a "predetermined" input which is fixed in period $t-1$ and that intermediate materials $M_{j,t}$ is a flexible input chosen every period. We depart from their framework in allowing labor $L_{j,t}$ to be a dynamic input, while GNR assume that labor is predetermined like capital. The timing of the model is such that firms enter period t knowing $(K_{j,t}, L_{j,t-1}, \omega_{j,t-1})$. They then observe $\eta_{j,t}$ and choose $L_{j,t}$ (which is allowed to depend arbitrarily on $L_{j,t-1}$ through adjustment costs or other factors) and $M_{j,t}$ (which does not depend on $M_{j,t-1}$). After input decisions are set, the firm observes $\epsilon_{j,t}$. We assume that firms can adjust wages in response to both shocks, but that firms are price takers in output markets and the market for intermediate materials.

[16]Using revenues as our measure of output implies that our measure of TFP is "revenue" TFP rather than "quantity" TFP and thus contains both variation in production efficiency, as well as potential variation in demand. We do not see this as a problem in our context, as we are agnostic about the source of the firm shock, as long as it is exogenous to input variation. We allow firms to adjust wages in response to shocks to both efficiency and demand, as both of these represent measures of firm-level risk which may be passed on to workers' wages. We choose to estimate revenue TFP since it allows us to include firms from the service sector which make up the bulk of Danish employment and economic activity.

cleaning activities of the remaining workers, the firm's output will likely go up, while the number of hours or employees will remain fixed.[17] This introduces significant bias into any estimates of firm productivity.

A second possibility is to use the total wage bill of the firm. In this case, a firm that uses more engineers than janitors will have a larger wage bill, potentially controlling for the difference in ability of these types of workers. There are two main problems with this approach. First, there is plenty of evidence that firms play a substantial role in the determination of wages and that workers with similar characteristics perceive different wages in different firms.[18] Second, by using the wage bill as a measure of labor quality, we are implicitly assuming that labor markets are perfectly competitive, and in such case, we should not expect to see any passthrough from firms' idiosyncratic shocks to workers' wages as wages would only depend on aggregate conditions.

Hence, neither the number of workers in a firm nor the wage bill are entirely satisfactory measures of the quality of the labor inputs hired by a firm. The estimates derived from our AKM model, instead, allow us to net out the effect of firms on the wage bill while not imposing any conditions on the structure of the labor market that induces the wages we observe in the data. In particular, the estimated value of the individual fixed effect and observable characteristics from equation (1), $\hat{\alpha}_i + \hat{\Gamma} X_{it}$, is a measure of the "quality" of a worker which is independent from the characteristics of the firm where she works (which are all soaked up by the firm-time fixed effect $\psi_{j(i,t)t}$). Using this measure for all workers in a particular firm, we define the *ability-adjusted labor input* as

$$A_{jt} = \sum_{i \in J_t} \exp\left(\hat{\alpha}_i + \hat{\Gamma} X_{it}\right) H_{ijt},$$

where J_t is the set of workers in firm j in period t and H_{ijt} is the number of hours worked by individual i in firm j in period t. Our ability-adjusted measure of firm productivity then comes from estimating

$$y_{jt} = f(k_{jt}, a_{jt}, m_{jt}) + \nu_{jt} \tag{6}$$

[17] In Chan *et al.* (2019b) we find that about 2/5ths of the adjustments in labor inputs in response to productivity shocks are changes in average labor input quality within the firm rather than changes in hours or number of employees.

[18] For instance, several papers using the AKM approach find that around 10% of the dispersion of workers wages is accounted for by fixed differences across firms. See for instance Barth *et al.* (2016); Song *et al.* (2019); Engbom and Moser (2018).

where $a_{jt} = \log A_{jt}$. Note that the estimation procedure still allows a_{jt} to be correlated with productivity ν_{jt} via η_{jt} and ω_{jt-1} but not ϵ_{jt}. We also define the *ability-adjusted log hourly wage,* as

$$\hat{w}_{ijt} = \psi_{j(i,t)t} + \xi_{ijt}$$

which is the component of worker i's hourly wage which is specific to their employment relationship with firm j in year t. We use this measure of ability-adjusted wages as the main dependent variable in the regression analysis in Section 4.

3.3 Selection Model

Most papers analyzing the impact of firms shocks on wages have focused on workers that maintain a stable employment relationship with their firm. However, the decision of a worker to stay in a firm is obviously endogenous and may depend on the shocks affecting the firms. Ignoring this endogenous selection into the sample of "stayers" will likely lead to biased passthrough estimates. For instance, suppose that after a negative shock a firm decides to reduce wages in order to reduce costs. If workers are more likely to leave a firm when faced with larger wage cuts, then focusing only on those workers that stay–and thus were less likely to have faced a large wage drop–would bias our estimates of passthrough towards zero, thereby overstating the degree of insurance provided by the firm.

In order to correct for this bias in our empirical analysis, we consider a simple model that describes the worker's job mobility problem given by

$$\begin{aligned}
\Delta w_{ijt} &= \mathbb{X}_{it}\Lambda + \epsilon^1_{ijt} && \text{if } \; u_{ijt} > 0 \\
\Delta w_{ijt} &= \text{unobserved} && \text{if } \; u_{ijt} \leq 0 \\
u_{ijt} &= \mathbb{Z}_{ijt}\delta + \epsilon^2_{ijt} && \\
D_{ijt} &= 1 && \text{if } \; u_{ijt} > 0, \\
D_{ijt} &= 0 && \text{if } \; u_{ijt} \leq 0.
\end{aligned}$$

In this setup, u_{ijt} represents the worker's net utility when she chooses to stay at firm j in period t relative to switching to a different firm or out of employment; w_{ijt} and $\mathbb{X}_{ijt}$ are stayers' log hourly wage and the observable characteristics which affect workers' wage growth. Z_{jt} are observable factors including $\mathbb{X}_{ijt}$, which affect the workers' utility of staying in their job. When the net utility from staying in the firm is negative, workers

switch out, so we do not observe their within-firm wage change and thus passthrough. We denote whether or not we observe the within-firm wage change by the indicator variable D_{ijt}.

Our strategy to correct for the selection follows the standard methods developed by Heckman (1979). Specifically, we assume that the joint distribution for the errors is given by:

$$\begin{pmatrix} \epsilon^1_{ijt} \\ \epsilon^2_{ijt} \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma^2 & \rho\sigma \\ \rho\sigma & 1 \end{pmatrix} \right].$$

Given this assumption, we estimate a first-stage probit model of the probability that a given worker stays at her firm as a function of $\mathbb{Z}_{ijt}$, obtaining $\hat{\delta}$. Then we calculate the fitted value of the latent variable $\hat{u}_{ijt}$ and compute the inverse Mills ratio $\hat{\lambda}_{ijt}$ as a function of $\hat{u}_{ijt}$. We then include $\hat{\lambda}_{ijt}$ in our subsequent regressions of worker wage changes on firms' productivity shocks to obtain a consistent and unbiased (though not asymptotically efficient) estimator of the passthrough from firms' shocks to wages.

Our identification strategy relies on having a reasonable exclusion restriction for the first stage that includes firm and worker variation which plays a role in the probability that workers will stay or leave their firm, but does not affect the growth rate of workers' wages should they choose to stay at the firm that period. In order to do this, we use the spousal linkages available in our dataset to create, for each worker, a set of marital status indicators and–for those with working spouses–measures of their spouse's employment status and firm shocks. Specifically, we include indicators for marriage status, separation, change of spouse and whether or not the individual's spouse is working if married. This last term is interacted with other spousal information including log wage, change in log wage, firm TFP and log TFP change, age, experience, and whether or not the spouse stayed in their firm for that period. We exclude information about the spouse of a worker if if the couple is working at the same firm. This gives us the following first-stage probit model,

$$\Pr(D_{ijt} = 1) = \Phi\left(\beta^d_p x_{ijt} + \beta^d_n x_{ijt} \times \mathbb{I}_{x_{jt}<0} + X_{it}\Lambda^d + Z_{jt}\Gamma^d + T_{it}\Omega^d + E_{it} \times S_{it}\Psi^d\right) \quad (7)$$

where x_{ijt} is a measure of firm productivity shocks (e.g.: $\Delta\nu_{ijt}$ or η_{ijt}), X_{it} and Z_{ijt} are worker and firm level observables, T_{it} is the set of marital status indicators, E_{it} is an indicator which equals 1 if the worker's spouse is employed, and S_{it} is a vector of observables for the spouse and the spouse's firm as described above.

The assumption for our choice of instruments is that when a worker gets married/divorced or his/her spouse has an income or employment change, this will affect the worker's decision of whether or not to keep working at their current firm. However, changes in marital status, spousal employment, or spousal wages should not affect the degree to which the worker's firm passes firm shocks on to the workers at that firm conditional on staying. The first column of Table III shows a few key parameter estimates from the first stage mobility regressions (equation 7) using total change in productivity, $\Delta\nu_{ijt}$. A few things stand out. First, we find that positive productivity shocks increase a worker's probability of staying, while negative shocks decrease the probability that a worker stays at the firm. In addition, negative shocks have a much larger effect on mobility than positive shocks. We also find that males, older workers and workers who have recently changed spouses are more likely to leave a firm, while being married, having longer tenure, having a spouse who stays at their firm, and having a spouse who experiences a positive TFP shock all increase the probability of staying. The second column of Table III displays similar results if we replace $\Delta\nu_{jt}$ by the persistent shock to firms productivity, η_{jt}. In the next section, we use these estimates–the inverse Mills ratio in particular–to correct for the endogenous selection of stayers.

4 Results

4.1 The Passthrough from Productivity Shocks to Wages

In this section we discuss our main results relating changes in workers' hourly wages to different measures of idiosyncratic firm productivity shocks. Table IV shows selected statistics for the main variables we use in our analysis. Panel A shows moments of the distribution of log hourly wage growth for our sample of workers. In our sample, the standard deviation of log wage growth for workers who stay at their firm is 0.18 (column 1), which is half of the dispersion in wage growth experienced by workers that switch jobs (column 2).[19] Panel B shows similar statistics for the worker-level (i.e.: employment weighted) distribution of firm TFP growth, and the distribution of the persistent and transitory shocks to firm productivity. The standard deviation of the persistent component is equal to 0.27, which is somewhat larger than the standard deviation of the

[19]By comparison, Kurmann and McEntarfer (2019) report a interquartile range of 11 log points which is close to our estimates. Relative to these authors, however, we find a much larger share of stayers that receive a wage cut.

transitory component.[20]. Panel C shows the same statistics as Panel B, but at the firm-level (not employment weighted). We use the moments from this final panel to calculate the monetary impact of a one standard deviation shock to productivity in the analysis below.

Our main estimates of the passthrough from firm shocks to wages are based on a series of worker-panel regressions that relate the change in workers' hourly wages to their firms' idiosyncratic productivity shocks. More precisely, our baseline specification is

$$\Delta\hat{w}_{ijt} = \alpha + \beta^{\nu}\Delta\nu_{jt} + Z_{jt}\Gamma + X_{jt}\Lambda + \rho\hat{\lambda}_{ijt} + \delta_t + \zeta_{ijt}, \tag{8}$$

where $\hat{w}_{ijt}$ is the ability adjusted log hourly wage of individual i in firm j and $\Delta\nu_{jt}$ is the change of log-TFP for firm j between periods t and $t-1$. The matrices Z_{jt} and X_{it} control for firm characteristics (e.g. lagged productivity, firm size, firm age, etc.) and worker characteristics (e.g. gender, age, tenure in the firm, wage level, ability, etc.) respectively, δ_t is a time fixed effect that controls for aggregate fluctuations in the economy, and ζ_{ijt} is the residual. We also include the estimated inverse Mills ratio $\hat{\lambda}_{ijt}$ obtained from the first stage estimates of equation (7). We estimate separate first-stage models for each of the passthrough specifications in this and all following sections. As we shall see, controlling for selection has important implications for the value of β^{ν}, our main parameter of interest, which measures the *average* passthrough from changes in firm productivity to wages.

We start by estimating the average passthrough measured by equation 8. Table V displays our main results. Column (1) shows there is significant passthrough from firm TFP shocks to hourly wages, with an elasticity of worker wages to firm productivity of 0.076. Quantitatively, this implies that a worker employed in a firm that experiences a one standard deviation increase in productivity (about 0.23 log points in our sample) receives an increase in average hourly wages of 0.018 log points. This change amounts to \$1,074 US dollars for the average full time worker in Denmark (see bottom panel of Table V) or about about 1.8% of their annual income.[21] Given that in a typical year around 20% of firms in our sample (which employ around 25% of all the workers in the

[20]By comparison, Guiso and Pistaferri (2020) reports standard deviations of about 0.05. As we show in this section, the passthrough estimates are quite inline with the rest of the empirical literature, indicating that in our context, firms provide a larger degree of insurance than the one implied by, for instance, Guiso and Pistaferri (2020)

[21]For this calculation we multiply the value of β^{ν} times the standard deviation of firm productivity growth times the average annual wage of the workers in the corresponding sample.

Denmark) experience a change in productivity of at least one standard deviation away from the mean, we conclude that idiosyncratic fluctuations in firm productivity represent an important source of fluctuations in workers' income.

Our estimates also allow us to separately analyze the passthrough of positive and negative productivity changes to wages. We do so by interacting $\Delta\nu_{jt}$ with an indicator variable which is equal to one if the corresponding change is negative, using the following specification:

$$\Delta\hat{w}_{ijt} = \alpha + \beta_p^\nu \Delta\nu_{jt} + \beta_n^\nu \Delta\nu_{jt} \times \mathbb{I}_{\Delta\nu_{jt}<0} + Z_{jt}\Gamma + X_{jt}\Lambda + \rho\hat{\lambda}_{ijt} + \delta_t + \zeta_{ijt}, \tag{9}$$

where β_p^ν measures the average passthrough from a positive change in ν_{ijt}, while $\beta_p^\nu + \beta_n^\nu$ is the average passthrough from a negative shock. The results are shown in column (2) of Table V. First, notice the coefficient for a positive change is slightly smaller than the average change displayed in column (1), but still statistically and economically significant. Second, and more importantly, the elasticity of wages to a negative change in productivity–the sum of the two coefficients–is substantially higher and equal to 0.11. This indicates that a one standard deviation change in TFP, conditional on this change being negative, generates a decrease in annual wages for the average Danish worker of 1,600 US dollars, which is almost twice the change in wages after a positive productivity shock of the same magnitude.

We then turn to analyzing the impact of transitory and persistent shocks to productivity on wages. These two types of shocks can have a distinct impact on workers as firms might be more likely to insure workers from variations in productivity that are perceived as transitory–e.g. a decline in sales because of unexpected bad weather–than from variations that are perceived as persistent–e.g. an increase in sales because of the implementation of a new online platform. Following the estimation approach introduced first by Guiso *et al.* (2005), most papers have consistently found that only persistent shocks to firms are passed to wages whereas transitory shocks do not have a significant impact (see Card *et al.* (2018) and Guiso and Pistaferri (2020) for recent reviews).[22] Here, we reevaluate the role of persistent and transitory shocks to workers wages by including in our baseline specification the measures of the persistent and the transitory

[22]One notable exception is Howell and Brown (2019) who find that a transitory cash flow shock to the firm–derived from government grants–significantly impacts workers' wages. The transitory shocks we study, however, differ from theirs in that a transitory cash flow can imply a persistent change in productivity if that leads to innovation or the incorporation of new technologies.

components of firms' shocks estimated in Section 3.2. In particular, we estimate

$$\Delta\hat{w}_{ijt} = \alpha + \beta^{\eta}\eta_{jt} + \beta^{\epsilon}\epsilon_{jt} + Z_{jt}\Gamma + X_{it}\Lambda + \rho\hat{\lambda}_{ijt} + \delta_t + \zeta_{ijt}, \tag{10}$$

where β^{η} and β^{ϵ} are the elasticity of wages to persistent and transitory shock to firms' TFP respectively and $\hat{\lambda}_{ijt}$ is estimated from a separate first-stage regression on η_{jt} and ε_{jt} rather than $\Delta\nu_{jt}$.

Column (3) of Table V shows the results. In contrast to most studies in the literature, we find that both transitory and persistent shocks have a significant impact on hourly wages, although wages are more than two times more responsive to persistent than to transitory shocks to firms' productivity. We then separate the impact of transitory and persistent shocks into their positive and negative parts, as we do for total productivity in equation 9. Similarly to what we find when we study total TFP growth, we find marked asymmetry. In fact, as column (4) shows, the impact of a negative persistent shock is twice as large as the impact of a positive persistent shock. In term of annual earnings, a decline in η_{jt} of one standard deviation generates a drop of \$1,500 US dollars, whereas an increase in η_{jt} of the same magnitude generates an increase in annual earnings of only \$700 US dollars. We find a similar asymmetric pattern for the transitory shock, with negative transitory shocks having a larger overall impact on wages than positive shocks, though the magnitudes are smaller than for persistent shocks.[23] Hence, we conclude that the passthrough from idiosyncratic productivity fluctuations is not only significant but also highly asymmetric, indicating that an important fraction of the changes in average hourly wages are due to changes in firm productivity.

The Importance of Selection

The evidence presented in Figure 1 suggests that the bias arising from endogenous worker mobility is large, significant, and asymmetric. In our context, selection biases the results if those workers experiencing larger wage cuts from a particular change in TFP are more likely to leave their firm (either by quitting to avoid a negative wage cut or by leveraging increased wage offers to move up in the job ladder) than those experiencing

[23] As mentioned earlier, the literature has found almost no role for transitory shocks to firms. Our results differ from the rest of the studies in the subject mainly because of our estimation strategy and not because of particularities of the data we use. In fact, we if we apply the method of Fagereng *et al.* (2017) in our data set, we find an elasticity of wages of 0.074 and 0.015 to persistent and transitory shocks to firms (both significant at the 1%). In comparison, Fagereng *et al.* (2017) finds elasticities of 0.071 and 0.018 respectively using Norwegian administrative data. Guiso *et al.* (2005) finds similar coefficients (0.070 and 0.0049) using Italian data.

smaller wage changes. In other words, job mobility serves as a way for workers to insure themselves from negative shocks to firms. In such cases, only those workers who did not receive a (large) change in wages will stay in their firm, biasing the impact of firm shocks towards zero.

To evaluate the extent of the bias, we repeat the previous analysis but without correcting for worker selection (i.e. we exclude the inverse Mills' ratio from our regressions). The results are shown in columns (5) to (8) of Table V. Overall, we find that selection biases the impact of firms' shocks to hourly wages towards zero. We also find that the bias is more significant for persistent than for transitory shocks. To see this, compare column (3) to column (7), where the elasticity is halved for persistent shocks but remains the same for transitory shocks. This is consistent with the timing of our model of firm productivity, which assumes that inputs are fixed prior to observing ϵ_{jt}. The impact of negative shocks is the most affected by selection, especially for persistent shocks: if we were to ignore selection one would conclude that negative shocks, even when they are persistent, have an elasticity of 0.022, six times smaller than the elasticity implied by our baseline estimates. Given the importance of properly controlling for selection, all the results that follow include a selection-correction term.

Persistence and Aggregate Shocks

We complement the previous analysis by studying, first, whether shocks to firms translate into persistent changes in workers' wages, and second, how the passthrough from idiosyncratic shocks to wages compares to the passthrough from industry or aggregate shocks.

Do firm shocks generate long lasting effects on workers wages? Intuitively, if shocks to firms only translate into a one period increase in workers wages (even in the shocks to firms are persistent), one should expect a large contemporaneous passthrough (the correlation between a shock in t with a change in workers wages between t and $t-1$), but a much smaller passthrough at longer horizons (for instance, the correlation between a shock to firms in t and a wage change between $t+4$ and $t-1$ must be closer to 0). To study the persistence of passthrough, we modify our baseline specification in (10) by extending the horizon of the wage change on the left hand side to $t+k$ periods where k can take values between 0–as in our baseline case–and 4. Importantly, we keep constant the period in which we measure firms' productivity shocks and other firm andworker observables. Note that our selection correction procedure changes as well, such that we

run separate first-stage regressions for each separate time horizon, where the dependent variable in the first stage is an indicator of whether the worker stayed at the firm for all $t-1$ to $t+k$ periods.

Figure 3 shows–on the y axis–the elasticity of worker wages to a persistent or transitory shock to firm productivity at different horizons. Each point on each figure represents a passthrough coefficient from a separate set of first and second stage regressions. In both panels, the x-axis corresponds to the periods over which the growth is calculated and the vertical lines are 95% confidence intervals for the corresponding regression coefficient. The left panel shows that passthrough from persistent TFP shocks not only is significant in the first year–our baseline estimate–but also persists after 4 years, with only a small decay in magnitude. In contrast, transitory shocks are, by nature, short-lived, but their effects do not disappear immediately after the shock, generating a small but still significant change in workers' wages even 2 years after the shock. However, by year 4 the effect is basically zero. As we show in the Appendix, these results are quite robust and persist if we separate positive from negative shocks (Figure A.2) or if we restrict our sample to a balanced panel of workers that stay in the same firm for all the four years after the shock (Figure A.3).

We conclude this section by discussing the differential impact of aggregate and industry shocks on workers' wages. Separating their effect is important as there might be general equilibrium effects that confound our passthrough estimates. Here, we follow Carlsson *et al.* (2015) and we first regress our firm-level productivity changes on a set of year dummies and calculate the residual change which is orthogonal to the aggregate cyclical variation in TFP. We then regress those residual changes on a full set of year-industry dummies. The predicted values from this regression give us our measure of industry-level TFP shocks, while the residuals are our measure of idiosyncratic firm-level changes in TFP. Finally, we regress changes in log hourly wages on these measures of firm- and industry-level productivity shocks. As column (1) of Table VI shows, the elasticity of wages to shocks for firms' idiosyncratic productivity is almost the same as in Table V, indicating that aggregate shocks play little role in our results (or that the elasticity of hourly wages to aggregate productivity shocks is close to 0). Changes in average productivity at the industry-level (denoted by $\Delta\nu_t^k$) have a significant impact on workers' wages, although the passthrough is less than half than the passthrough from idiosyncratic shocks. Furthermore, if we separate positive from negative shocks, we find that only negative industry productivity changes have an impact on workers' wages.

The economic impact is small since there is little variation in industry-level productivity relative to aggregate and idiosyncratic variation.

In conclusion, in this section we have shown that idiosyncratic shocks to firms have a significant and persistent impact on workers wages, which depend not only on the nature of the shocks (persistent versus transitory) but also on the sign(whether this is positive or negative). In the next section, we exploit the richness of our dataset to explore several levels of heterogeneity which will help to shed light on the mechanisms that can generate the large asymmetric passthrough we observe in the data.

5 Heterogeneous Passthrough

In order to better understand the channels that might explain why hourly wages change after a shock to idiosyncratic firm productivity, in this section we study how the passthrough varies across several key characteristics of the population of workers, such as income level, measured ability, age, and tenure within the firm (Section 5.1). On the firm side, we separate companies by their productivity level, labor market power, and relative size (Section 5.3). Finally, we study whether the passthrough is state-dependent and changes between recession and expansion years. The main conclusion of this section is that passthrough is highly heterogeneous and varies substantially across groups and over the business cycle.

5.1 Worker Heterogeneity

Worker Wage Level

We first ask whether workers in different levels of the wage distribution are differentially exposed to the shocks of the firms where they work. This is important for at least three reasons. First, low-income individuals typically have low wealth holdings and are more likely to be credit constrained. Then, to the extent that idiosyncratic shocks to firms represent uninsurable income risk for the workers, a higher passthrough for those workers with the least ability to save might have significant welfare implications. Second, variations in passthrough across income levels might help to explain why individuals at the top and bottom of the income distribution seem to face larger fluctuations in labor earnings than individuals in the middle of the distribution (Guvenen *et al.*, 2015). Third, differences in payoff schemes might imply differential passthrough for workers at different

positions within the firm. In particular, it is possible that CEO earnings or managers–which are more likely to be at the top of the income distribution–are more correlated to firm performance than regular workers. Hence, one would expect that high-income individuals are subject to a higher passthrough.

In order to shed light on these issues, we separate workers into different quintiles based on their (lagged) hourly wage and estimate the effect of persistent and transitory shocks to firm TFP on wages within each of these groups. Figure 4 summarizes our results. The differences in passthrough between low and high wage workers after a persistent shock to the productivity of their firms are substantial (left panel of Figure 4): The elasticity of hourly wages to a persistent shock to firms' TFP for workers in the fifth wage quintile is more than three times as large as the elasticity of hourly wages for workers in the first quintile of the distribution. Quantitatively, we find that top quintile workers gain six times more in annual income than bottom quintile workers ($1,763 US dollars versus $285 US dollars, which represent 1.9% and 0.8% of the within-group average annual income respectively) when both groups receive a persistent shock to TFP of one standard deviation.

As we discussed earlier, the effect of negative persistent shocks on workers' wages is stronger than the effect of positive shocks. This is true for all workers across the income distribution, but especially for workers at the top quintile: a negative shock to the persistent component of firm productivity generates a drop in annual wages of $400 US dollars for individuals in the first quintile of the wage distribution (about 1.1% of the annual income in the group), but a drop of $3,200 US dollars for workers in the top quintile (or about 3.4% of the average annual income in the group). In other words, we find that high wage workers experience more gain and more pain when their firms experience persistent TFP shocks, which is consistent with the idea that worker compensation is increasingly linked to firm performance as workers move up the income distribution.[24] The quantitative effect of transitory shocks to TFP is considerably smaller than the effect of persistent shocks (right panel of Figure 4). This is in line with our baseline results of persistent shocks having a more prominent effect on wages. Furthermore, relative to a persistent shock, the effect of a transitory shock on wages is much less heterogeneous across the income distribution.

[24]There is also suggestive evidence that high wage workers and top executives can suffer substantial income losses, especially during a deep recessions like the past financial crisis (Guvenen *et al.*, 2014) and such risk can have important implication, for instance, for asset prices (Schmidt, 2016).

Worker Ability

We then focus on how passthrough varies across different ability levels. Recall that we define worker ability as a combination of their individual fixed effect and observable characteristics: $\exp(\hat{\alpha}_i + \hat{\Gamma} X_{it})$. This measure of ability encapsulates variations in income across individuals that are independent of firms. Similarly to our analysis of wages, we divide workers into ability quintiles and estimate passthrough elasticities within each of these groups.

The left panel of Figure 5. shows the passthrough elasticity of persistent TFP shocks on wages which is clearly increasing in in worker ability. On average, the highest ability quintile workers gain \$1,444 US dollars (1.7% of their average annual income) in response to a one standard deviation shock, while lowest quintile workers gain only \$335 US dollars on average in response to the same shock. The difference in passthrough across worker ability quintiles is even stronger when firms experience negative persistent shocks. Workers at the top ability quintile lose \$2,149 US dollars on average (2.5% of their annual income) in response to a one standard deviation negative persistent shock while those at the bottom quintile lose \$529 dollars on average (1.3% of their annual income). Note that the top quintile loses more in terms of average annual income than the fourth quintile (\$2,149 versus \$2,132 US dollars), however the top quintile is actually less exposed to negative shocks than the 4th quintile, with a passthrough elasticity of 0.130 versus 0.181 (2.5% of annual income versus 3.5% for quintile 4). Finally, similarly to previous results, we find that the passthrough from negative shocks is higher relative to positive shocks. This is true for workers in every ability quintile.

We then turn to the impact of transitory shocks, displayed in the right panel of Figure 5. It is immediately clear from the graph that the elasticity of wages to transitory shocks is considerably smaller than the elasticity to persistent shocks, and that the effect across different ability quintiles is not very different. Workers at the top quintile gain \$403 dollars (0.5% of annual income) when their firm faces a positive one standard deviation transitory shock, while workers at the bottom gain \$201 (0.5% of their annual income) for the same shock. When firms experience a negative one standard deviation shock, workers at the top of the ability distribution lose \$873 dollars (1%) while workers at the bottom lose \$201 dollars (0.5%). The asymmetry between the effects of a positive and negative transitory shocks is of much smaller magnitude compared to the case when firms encounter persistent shocks.

Overall, workers with high ability have higher passthrough relative to low ability workers. This is true when a firm faces both positive and negative persistent shocks, however, the wage response to negative TFP shocks is stronger than positive shocks. This may reflect that workers with higher ability are typically working at higher ranked positions within a firm and therefore receive a bigger bonus when firms are doing well and receive larger reductions in bonuses when firms face negative shocks.

Worker Age

Workers may be more or less exposed to firm shocks depending on their age. On the one hand, one might expect that older workers are likely to be more experienced on average or have longer tenure and therefore are potentially more insured by firms than workers who have just entered the firm–who are typically younger. On the other hand, workers with higher tenure might receive higher increases in income after a positive productivity shock if the firm borrowed from them in the past, of if their compensation is more linked to firm performance as they move up in the firm compensation structure. In order to understand whether workers of different ages are more or less subject to differences in passthrough, we separate workers into five age groups: 15 to 29 years old, 30 to 39 years old, 40 to 49 years old, 50 to 59 years old, and 60 years and older. We then estimate the effect of persistent and transitory shocks to firm TFP on wages within each of these groups, correcting for selection as described in section 3.3.

Overall, we find that young workers experience higher losses and lower gains while older workers face the opposite, except perhaps for workers who are close to retirement. The left panel of Figure 6 shows the effects of persistent TFP shocks (η_{jt}) on workers' wages across different age groups, and the right panel shows the effects of the transitory TFP shocks (ϵ_{jt}). On the one hand, passthrough is weakly increasing in worker's age when the persistent shocks are positive. In other words, older workers get a higher wage increase than younger workers when firms face a positive TFP shock, though the difference is not very large. Workers who are between 50 and 59 years old receive an average increase in their annual income of \$806 US dollars (1.3% of their annual earnings) when firms experience a one standard deviation positive shock, while workers who are below 29 years old gain \$554 (1.2% of their annual earnings) in response to a persistent TFP shock of the same magnitude and sign.

On the other hand, the response of wages to persistent TFP shocks is decreasing in workers' age (for all age groups except 60+) when the shocks are negative. Workers who

are between 50 and 59 years old lose $1,544 on average in response to a one standard deviation negative shock to persistent TFP (2.5% decrease in annual income), whereas workers who are 29 years old or younger lose $1,628 on average for the same shock (3.4% of their annual income). Considering that young workers typically have lower incomes and do not have much savings, a low positive passthrough and high negative passthrough might have important implications for their welfare. In contrast, the older group of workers (those 60 years or older) has much higher passthrough for both positive and negative shocks relative to other age groups.

Finally, the right panel of Figure 6 shows the effects of transitory TFP shock on wages. As before, the effect of transitory shocks are much smaller and much flatter across age groups than the effects of persistent shocks. The effects for a one standard deviation transitory shock on workers wage changes range from a wage gain of $67(for workers who are 60 or older) to $251 US dollars (workers who are 29 years or younger). The effects of negative shocks are larger: A one standard deviation negative transitory shock decreases young workers' (15 to 29 years old) annual wages by $352 on average, and $570 for older workers (50 to 59 years old).

Worker Tenure

We have shown that the passthrough differs substantially across age groups. There may be many reasons behind this finding. For instance, it is well known that young workers tend to move across firms much more than older workers (Topel, 1991). Hence, older workers will have also a longer tenure within the firm, which might drive differences in passthrough. In order to separately investigate the effect of tenure from the effect of age, in this section we estimate our baseline specification within tenure groups. In particular, we divide workers into five groups: workers with tenure equal to 2 years or less, tenure between 3 and 4 years, between 5 and 7 years, between 8 and 14 years, and 15 years or more. We choose these cutoffs so that our sample of workers is split into roughly equal-sized groups.

The left panel of Figure 7 shows the elasticity of wages to a persistent shock for firms' idiosyncratic productivity. We find that the level of passthrough is roughly hump-shaped for both positive and negative TFP shocks. When firms experience a positive one standard deviation shock, workers of 15 or more years of tenure see an increase of $823 (1.3% of annual income) on average whereas workers with 2 years or less only gain $436 dollars (0.8% of annual income). When the shocks are negative, workers with

medium tenure (between 5 and 7 years) lose the most with a negative one standard shock generating a decline of $2,116 US dollars in their annual average income (3.4% of income). For transitory shocks (right panel of Figure 7) the heterogeneity in passthrough across workers in different tenure groups is not significant, and the magnitude is relatively small.

5.2 Switchers

So far we have focused on the effect of TFP shocks on stayers, that is, workers who maintain a stable employment relationship with a firm for the two years over which the change in TFP is calculated. This is a natural starting point as changes in wages for continuing workers can be tied more easily to changes in firm productivity. Moreover, this is the group of workers on which the literature has mostly focused. In this section, we extend our analysis to take into account the effect of idiosyncratic firm-level productivity changes on the wages of those workers that move across different employers, or switchers. We define switchers as those workers that change main employers between two consecutive years. This is a large group of workers: in our sample, around 20% of workers change employer in any given year. [25]

We start by looking at the distribution of log-TFP across the wage growth distribution for switchers. The top panel of Figure 8 shows the distribution of log hourly wage growth for our sample of job switchers(green bars) relative to the distribution of hourly wage growth for stayers(navy bars) .The dispersion of hourly wage growth for switchers is much greater, with a larger fraction of workers in the tails of the distribution. This higher wage growth dispersion may be explained, in part, by the fact that switchers are transitioning between firms of different productivity. This is shown in the bottom panel of Figure 8 where we plot (on the right axis) the average log-TFP of the two firms between which workers are transitioning, labeled as Old (red circles) and New (black squares) firm respectively. In particular, each black square is the average log TFP of the firms *into which* workers of that wage growth percentile switched, while each red circle is the average log TFP of the firms *out of which* workers of that wage growth

[25] Unfortunately, our annual data do not allow us to distinguish whether an individual passed through an unemployment spell prior to joining a different employer or had a direct transition between employers. Therefore, we put aside issues related to voluntary or involuntary separations and we treat all workers who make annual employer-to-employer transition the same. A register complementary to our data contains daily job spell histories. We are in the process of merging this dataset to our main sample in order to study how firm productivity shocks impact workers transitions between jobs and across employment status.

percentile switched. The patters are striking with a clear difference between negative and positive wage changes. Workers that receive a cut in hourly wages of 25 log points in their new firm relative to their old firm, move on average to firms which are 10 log points less productive. There is also a group of workers that, although they experience a wage cut of between 20 and 0 log points, move to firms with higher average productivity, potentially motivated by higher wage growth potential. Most noticeable is that workers that experience an increase in hourly wages do move, on average, to firms with much higher productivity, especially for those workers experiencing an increase in wages of more than 50 log points. For these workers, the average difference in productivity is about 50 log points.[26] These results strongly indicate that workers do move from low to high productivity firms to obtain higher wages, and at least a fraction of the the increase–or decrease–in wages is due to the productivity differences between firms.[27]

To further study the impact of firm productivity on the wages of the workers that move across firms, we run a set of OLS panel regressions in which the dependent variable is the change in real wages for an individual between two consecutive years and the key independent variable is the change in the TFP of the firm in which the individual works. Notice that for switchers the interpretation of a positive or a negative productivity shock is different than for stayers. For the latter group, it represents an *unanticipated* change in productivity in the firm in which they work, whereas for switchers it captures the *unanticipated* difference in productivity between two different firms. Hence, a positive TFP change for a switcher means that the individual moved to a firm with higher TFP relative to the firm at which she used to work, and this change is independent of the actual change in productivity experienced by any of the firms. For instance, it is possible that the transition was motivated by a productivity decline in the firm of origin, or an increase in the productivity of the new firm that poached the worker, or both. To capture these differences we modify our baseline specification to include in the regression the shocks to the productivity of both of the firms the individual is transitioning. In particular we

[26] Appendix Figure A.4 shows similar differences when looking at different percentiles of the distribution of log-TFP. In particular, the higher average productivity of switchers' new firms is not driven by a handful of highly productive firms that are offering higher wages, but rather the entire distribution of new firms is shifted to the the right

[27] Interestingly, workers tend to move to firms with positive TFP *growth* independently of whether hourly wage growth is positive or negative. This is shown in the top panel of Figure A.5 in the appendix. The right axis displays the within bin average TFP growth for the new and old firms for switchers. The bottom panel shows different percentiles of the TFP growth distribution. This indicates that expanding firms (those with positive productivity growth) capture workers from other firms, even from those firms that are of higher–but declining–average productivity.

estimate

$$\Delta\hat{w}_{ijkt} = \alpha + \beta_p^{\eta}\eta_{jkt} + \beta_n^{\eta}\eta_{jkt} \times \mathbb{I}_{\eta_{jkt}<0} + \beta_p^{\varepsilon}\varepsilon_{jkt} + \beta_n^{\varepsilon}\varepsilon_{jkt} \times \mathbb{I}_{\varepsilon_{jkt}<0}$$
$$+ Z_{jt}\Gamma_1 + Z_{kt}\Gamma_2 + X_{it}\Lambda + \rho\tilde{\lambda}_{ijt} + \delta_t + \zeta_{ijkt}$$

where $\Delta\hat{w}_{ijkt}$ is the change in real log hourly wages of an individual that works in firm j and moved from firm k. Hence, in this case, η_{jkt} is defined as the unanticipated change in persistent TFP between the old firm and new firm given by $\eta_{jkt} = \omega_{jt} - \mathbb{E}[\omega_{kt}|\omega_{kt-1}]$. The matrix Z'_{jt} includes firm $j's$ characteristics such as size and age. Similarly, the matrix Z'_{kt} includes firm $k's$ characteristics and lags of productivity. As before, the main coefficients of interests are β_p^{η} which captures the elasticity of a change in wages in response to a positive shock in persistent TFP for the individual, and β_p^{ε} which reflects the elasticity of a change in wages in response to a positive transitory TFP shock. The elasticity with respect to a negative persistent shock is $\beta_p^{\eta} + \beta_n^{\eta}$ and is $\beta_p^{\varepsilon} + \beta_n^{\varepsilon}$ for negative transitory shocks.[28]

Column (3) of Table VI shows the results for this analysis. Notice that the elasticity of switchers' wages to firms' TFP shocks is smaller than for stayers (compare to column (4) in Table V) but the dollar value of the shock is much larger for switchers (bottom panel of Table VI)

The large difference in dollar values between switchers and stayers is mainly due to the differences in the dispersion of TFP changes for stayers and switchers, as well as their differences in average wage. For example, the elasticity of wage growth to persistent TFP shocks is much bigger for stayers than switchers when they face negative shocks (0.131 versus 0.027), but the average wage loss from a one standard deviation within-firm negative TFP shock for stayers is smaller than the loss for switchers who experience a persistent one standard deviation firm-to-firm drop in TFP (compare \$1,495 versus \$1,914 US dollars, or 2.5% of annual average income versus 3.4% annual average income). Switchers also experience much larger wage increases than stayers: a one standard deviation increase in firm-to-firm productivity is associated with a \$2,099 US dollars annual wage gain for switchers compared to \$688 dollars for stayers that experience an increase in productivity of the same (relative) magnitude. These results reflect

[28] We control for selection in this regression by including the inverse Mills ratio $\tilde{\lambda}_{ijt}$ which is estimated from a first stage model similar to equation 7with the exception that D_{ijt} is instead an indicator which equals 1 if the worker moved to a different firm in period t.

that workers often move up or down in the wage ladder when they decide to switch jobs as is evident from Figure 8. One remarkable difference is that average passthrough for switchers is *symmetric,* which is quite different from the asymmetric passthrough we observed for within-firm shocks. This suggests that the within-firm passthrough asymmetry is driven by interactions between the firm and worker themselves, rather than anything inherent to wage or productivity differences. Workers climbing up or down the productivity ladder gain and lose equally regardless of the shift in relative productivity.

5.3 Firm Heterogeneity

Firms play a central role in determining individual wages. While a large literature has examined the role of firms in explaining dispersion in wages across observationally similar workers, there's still much we don't know about how or why wages vary across firms. Part of the reason may be that some fundamental characteristics of the firms play a role in determining the degree to which they insure their workers from firm-level risk. In order to better understand why some firms pay different wages to similar workers, in this section we examine how passthrough may differ across firms which differ in terms of productivity, age, size and market power. For example, empirical evidence suggests that highly productive firms, which are typically larger, and older are better equipped to bear fluctuations in productivity or demand and thus provide insurance for their employees.[29] Low productivity firms may not have the resources or flexibility to insure their workers, instead having to pass some of those shocks on to their workers. Young firms, or those with low productivity, may also be credit constrained and so unable to absorb their own firm shocks as well as larger, more productive firms, instead being forced to reduce wages to weather those shocks.

Firm Productivity Level

In order assess how passthrough varies for firms of differing productivity we proceed as we did when examining worker heterogeneity in the previous section and separate firms into five quintiles based on the level of their lagged TFP (ν_{jt-1}). We then run our baseline regressions (both stages) separately within each group. The left panel of Figure 9 shows our results. We find that passthrough from persistent shocks to firms (both negative and positive) is roughly decreasing in total productivity, especially for the top 3 quintiles. For example, workers employed at firms in the lowest productivity quintile

[29] This is true using standard measures of productivity as in Syverson (2011) and using labor-corrected measures of productivity as in this paper and Chan *et al.* (2019b).

gain (lose) \$789 (\$1,427), or 1.5% (2.8%) in annual income on average when their firm experiences a positive (negative) persistent shock of one standard deviation.

Workers employed in firms at the highest quintile of the TFP distribution see much smaller wage changes. On average, workers gain \$251, or 0.4% in annual income (lose \$537, or 0.8% annual income) dollars when their firm experiences a one standard deviation positive (negative) persistent shock. Similar to the results from the previous sections, negative passthrough is considerably larger than positive passthrough once we take into account selection, though passthrough from negative and positive persistent shocks are not statistically different for high productivity firms. Furthermore, the effect from transitory shocks is relatively insignificant relative to the effect from persistent shocks especially for high productivity firms where the (average) passthrough from transitory shocks is effectively zero. This result is consistent with the intuition that high TFP firms (which are typically larger and potentially have better access to financial markets) should be more capable of self-insuring against shocks, and thus providing better insurance for their employees as well.

Market Power

An increasing number of papers indicate that firm labor market power and concentration may have increased in the United States over the last few decades (David *et al.*, 2017; Dorn *et al.*, 2017). Such increases in concentration might have important consequences for mark-ups or the share of total output received by workers (Berger *et al.*, 2019; Lamadon *et al.*, 2019; Chan *et al.*, 2019a). Hence, differences in labor market concentration–a measure of labor market power–may also have an impact on firm-level passthrough from TFP shocks to wages. The intuition is that the more labor market power a firm has, the greater their ability to mark-down wages relative to marginal productivity and potentially decrease wages when facing negative shocks. We ask whether firms with the largest share of employment within a local labor market pass a higher or lower share of their productivity shocks to wages. In particular, we define the labor market power of firm j as the employment share of firm j within a year-municipality bin. We rank all firms in terms of their employment share and partition them into five quintiles.

The left panel of Figure 10 shows how persistent shocks affect worker wage growth across different levels of market power. We find that both negative and positive passthrough is decreasing in the share of employment held by the firm within a local labor market.

In responding to a one standard deviation productivity shock, workers in firms in the highest market power quintile see on average a \$829 decline in wages when the shock is negative and a \$335 increase when the shock is positive. These numbers increase significantly for workers employed by firms with lower market power: Workers at firms in the lowest quintile see a \$1,947 wage drop in response to a one standard deviation negative shock, and \$990 more in response to a positive shock. The results are again similar to previous ones where negative shock passthrough is much stronger than positive passthrough, and persistent shocks have a much larger effect than transitory shocks. We find similar results if we define a labor market by year-industry bins instead of year and municipality. This suggests that instead of leveraging market power to increase passthrough to workers as a method of self-insurance, firms with more local labor market power may offer higher income risk insurance to their employees as a form of amenity value, perhaps contributing to their larger share of employment.

5.4 Aggregate State Dependance

Like the rest of the world, Denmark was hit by a severe economic downturn in 2008. The decline in Danish GDP was under-way at the beginning of 2008 and was accompanied by a large drop in labor market hiring and an increase in separation rates. Did the passthrough from firms' idiosyncratic shocks to wages change during the Great Recession? To investigate if this is the case, we estimate two sets of passthrough regressions. The first pools observations from the two years of the great recession (2008 and 2009). The second pools all of the other (expansion) years in our sample (excluding 2002-2003, which also experienced a milder recession). The results are shown in columns (4) and (5) of Table VI.

First, notice that during expansion years, the passthrough coefficients are quite similar to those obtained from baseline results–compare to column (4) in Table V. This is not surprising considering that most of the years in our analysis are expansion years. Second, recession years show a different pattern, especially for the impact of persistent productivity shocks on wages. In particular, the passthrough from negative shocks remains almost unaltered between these two periods (recall that to calculate the impact of a negative shock one must sum the two passthrough elasticities: $\beta_p^\eta + \beta_n^\eta$). In other words, firms that receive a negative idiosyncratic productive shock during a recession do reduce the wages of their workers. In contrast, the passthrough from positive shocks becomes insignificant and almost zero, indicating that firms which get a positive productivity

shock did not pass that increase to their workers. Passthrough from transitory shocks, on the other hand, does not seem to vary much across the business cycle. Overall, we find that the passthrough from positive firm shocks to worker wages is state-dependent, whereas the passthrough from negative shocks is not.

Similarly to the results presented by Grigsby *et al.* (2019)–who find that during the Great Recession in the United States, the share of workers receiving a positive change in their wages declined whereas the share of workers receiving a negative change increased– our results suggest that recessions are not periods in which firms are unable to cut wages when facing an idiosyncratic negative shock. Rather, firms during recessions seem unwilling to increase wages when facing a positive idiosyncratic shock. Hence, wages during recessions may appear to be less flexible than in expansions. This is not because firms cannot decrease wages– as would be the case, for instance, if there is a union keeping wages up or because the firm is worried about maintaining worker effort. Instead, firms do not need to increase the wages of their workers when they receive a positive productivity shock. This could happen, for instance, if during a recession the outside options of worker decline–e.g. there are fewer vacancies being posted–reducing the bargaining position of the worker.

5.5 Alternative Measures

Our empirical approach differs in several different ways to the standard methods used in the rent-sharing literature. In this section, we examine how each of these factors contributes to our results. To do this, we begin with a simple OLS regression of changes in (log) total annual income on changes in (log) firm value added, controlling for individual and firm observables as above. As shown in column 1 of Table VII, we find significant passthrough from changes in value added to annual income–an elasticity of 0.079 which implies that a one standard deviation change in value added leads to an average change in income of $1,911 US dollars. However, this effect could be due to a number of factors. The change in annual income could be due to a change in hours worked by the individual, either voluntarily or because of a change in labor demand by the firm.

The change in value added also includes planned shifts in labor demand, which means that a significant portion of the measured elasticity may be the mechanical link between changes in labor captured by changes in value added, and shifts in hours for workers captured in annual income. Column 2 shows the results of regressing changes in annual income on changes in residual value added, which is the predicted residual from a re-

gression of (log) value added on logs of firm capital and labor (measured in full-time equivalents). This strips variation in inputs out of the firm shock and reduces the elasticity to 0.063. However, the change in annual income still combines changes in hourly wage and hours on the worker side.

To decompose how much of the passthrough from shocks to income is due to extensive-margin adjustment in labor demand versus changes in the wage rate, we change the dependent variable to be changes in the log hourly wage (column 3 of Table VII). We find that a little more than half of the passthrough to annual income from changes in residual value added is due to changes in the hourly wage, while slightly less than half is due to changes in hours worked (we find similar results when using our more robust measures of firm shocks and wages).

When we additionally eliminate variation in worker ability at the firm level by using our ability-adjusted measure of labor input, a_{jt}, when calculating the value added residual (column 4), passthrough decreases from 0.035 to 0.032. Since passthrough and firm shocks may be related to worker ability, we then add in controls for individual ability (column 5) and find a significant increase in passthrough to 0.042. Finally, column 6 shows the results when we use our fully corrected measure of firm shocks–changes in AKM-adjusted TFP ($\Delta\nu_{jt}$) which unlike the value added residuals from the other regressions is allowed to be correlated with input adjustments. This increases the estimated passthrough to 0.046, which matches the uncorrected passthrough estimate in column 4 of Table V. These results indicate first that failing to correct for changes in hours will lead to significant over-estimates of passthrough, while not correcting for worker-level ability and mismeasuring firm shocks will significantly under-estimate it.

6 Conclusion

In this paper, we offer new evidence on the effect of changes in firms' productivity on workers' wages. Using high-quality employer-employee matched administrative panel data from Denmark we address two important issues which have been under-addressed by the literature so far: the effect of selection and the impact of changes in firm-level productivity for workers that switch between firms. Moreover, we provide a more direct measure of firm' total factor productivity which is plausibly exogenous to wage setting and labor demand, and we explore several degrees of heterogeneity among firms and workers types. To control for selection, we use a novel approach that exploits employment

and income information of worker's spouses to estimate the probability that an individual stays in the same firm during a particular year. We find that controlling for selection has a major impact in the passthrough estimates from TFP shocks to wages. To estimate firm productivity shocks, we extend the literature by allowing for imperfect markets and using a two-sided fixed effect approach to control for unobserved variation in labor quality.

In general, we find that the passthrough from firms' TFP shocks to workers' wages is statistically and economically significant: After we have controlled for selection, we find that a worker in a firm that experiences TFP growth of one standard deviation sees her annual earnings increase by $1,100 US dollars which is around 2% of Danish income per capita. Most of this effect is driven by persistent shocks to firms' productivity. Furthermore, there is a substantial asymmetry in the passthrough from positive and negative shocks: the elasticity of worker's hourly wage to a negative shock to firms' idiosyncratic productivity for stayers is almost two times as large as the elasticity to positive shocks. In other words, workers are more exposed to negative than positive shocks to firms' productivity.

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Table I – Sample Summary Statistics

	2000	2005	2010
Panel A: Workers			
Obs.	469,922	653,283	625,237
% Women	28.0	30.0	31.0
% High School	33.7	29.6	27.4
% Age groups			
Below 25	8.69	6.7	8.1
25-35	30.6	26.7	21.4
36-45	27.0	30.9	31.4
46-55	23.3	22.3	25.4
Above 55	10.3	13.4	14.0
Annual Labor Earnings			
Mean	49,513	53,104	54,176
P10	34,544	35,954	35,954
P50	48,533	51,534	52,052
P90	77,653	83,283	87,553
Hourly Wages			
Mean	30.35	32.23	32.88
P10	20.97	21.82	21.82
P50	29.46	31.59	31.91
P90	47.13	50.55	53.14

	2000	2005	2010
Panel B: Firms			
Obs.	29,561	45,180	48,289
Firm Age: % Share of Firms			
<5	8.9	10.9	11.4
5-10	23.5	44.3	48.5
10+	67.6	44.9	40.1
Firm Age: Average Employment			
<5	6.2	6.3	5.0
5-10	35.7	33.9	34.9
10+	58.2	59.9	60.1
Firm Size: % Share of Employment			
20	83.0	84.1	87.4
20-100	13.9	13.1	10.4
100-1000	3.0	2.6	2.2
1000+	0.1	0.1	0.1
Firm: Size: % Share of Employment			
20	24.3	25.5	28.2
20-100	28.1	28.8	26.6
100-1000	36.7	35.2	33.3
1000+	10.8	10.5	11.8

Table I shows different statistics for workers in our baseline sample. All monetary values are converted to US dollars in 2010. In order to avoid the disclosure of any sensitive information, we report the mean of the observations *within* a percentile-band rather than the individual observation at the percentile cutoff.

Table II – Decomposition of the Variance of Log Hourly Wages Using AKM

	1995-2002	2003-2010	Pooled
Worker Heterogeneity	50%	52%	51.0%
Firm Heterogeneity	11%	11.5%	11.3%
Wage Sorting	1.2%	0.9%	1.0%
Wage Sorting Correlation	0.01	0.01	0.02

Note: Table II presents the decomposition of log hourly wages variation using the AKM estimator for two time intervals and for the pooled sample. The AKM estimator uses information for all the firms that a individual worked for during a year.

Table III – First Stage Probit Estimates for Selection Model

Variable	Pr(Staying in Firm)	
	(1)	(2)
$\Delta\nu_{jt}$	.028*** (.005)	
$\Delta\nu_{jt} \times \mathbb{I}_{\Delta\nu_{jt}<0}$	.977*** (.004)	
η_{jt}		.313*** (.006)
$\eta_{jt} \times \mathbb{I}_{\eta_{jt}<0}$		1.111*** (.004)
Age	-.003*** (.001)	-.004*** (.001)
Male	-.132*** (.002)	-.154*** (.002)
Lag Tenure	.040*** (.000)	.040*** (.000)
Married	.027*** (.003)	.026*** (.003)
Change Spouse	-.119*** (.011)	-.119*** (.012)
Spouse's Firm's TFP (ν_{jt})	.017*** (.004)	.011*** (.004)
Spouse Stayer	.028*** (.003)	.026*** (.003)
Obs. (M)	7.04	7.04

Notes: Table III shows selected parameter estimates from our first-stage Probit model. $*p < 0.1, **p < 0.05, ***p < 0.01$. Robust standard errors are clustered at the firm-level.

Table IV – Summary Statistics of Hourly Wage and Productivity Shocks

	Panel A: Workers		Panel B: Workers			Panel C: Firms		
	Δw_{ijt}		$\Delta\nu_{jt}$	η_j	ϵ_{jt}	$\Delta\nu_{jt}$	η_j	ϵ_{jt}
	Stayers	Switchers	Stayers					
Mean	0.02	0.07	0.00	0.02	0.01	0.00	0.00	0.00
Sd	0.18	0.36	0.26	0.27	0.20	0.24	0.19	0.17
P10	-0.14	-0.30	-0.25	-0.27	-0.16	-0.23	-0.16	-0.17
P25	-0.05	-0.11	-0.12	-0.13	-0.07	-0.10	-0.08	-0.08
P50	0.01	0.06	0.00	0.00	0.01	0.00	0.00	0.00
P75	0.08	0.23	0.12	0.14	0.09	0.10	0.07	0.08
P90	0.18	0.46	0.26	0.34	0.18	0.22	0.19	0.17
Obs. (M)	6.47	0.56	6.47	6.47	6.47	0.57	0.57	0.57

Table IV shows sample statistics for workers hourly wage growth and firms productivity shocks. To avoid the disclosure of any sensitive information, percentiles are reported as the mean of all observations *within* a one-percentile band around the percentile of interest.

Table V – Passthrough from Firm TFP shocks to Wages

Dep. Variable	Change of Log Hourly Wages, $\Delta\hat{w}_{i,j,t}$							
	Selection Corrected				Uncorrected			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Specification:	All	Pos/Neg	All	Pos/Neg	All	Pos/Neg	All	Pos/Neg
$\Delta\nu_{jt}$	.076***	.060***			.046***	.062***		
	(.004)	(.004)			(.003)	(.004)		
$\Delta\nu_{jt} \times \mathbb{I}_{\Delta\nu_{jt}<0}$		.053***				-.032***		
		(.005)				(.005)		
η_{jt}			.077***	.061***			.033***	.044***
			(.007)	(.004)			(.004)	(.004)
$\eta_{jt} \times \mathbb{I}_{\eta_{jt}<0}$				.070***				-.022***
				(.007)				(.009)
ϵ_{jt}			.034***	.025***			.034***	.032***
			(.003)	(.005)			(.003)	(.004)
$\epsilon_{jt} \times \mathbb{I}_{\epsilon_{jt}<0}$				.018**				.007
				(.008)				(.009)
$Mills_{it}$	-.219***	-.278***	-.188***	-.262***				
	(.014)	(0.015)	(.023)	(.013)				
R^2	.78	.78	.79	.79	.78	.78	.78	.78
Obs. (M)	6.47	6.47	6.47	6.47	6.47	6.47	6.47	6.47
Monetary Value of a Shock to Firm TFP (US$ 2010)								
$\Delta\nu_{jt}$	$1,075				$655			
$\Delta\nu_{jt} > 0$		$840				$873		
$\Delta\nu_{jt} < 0$		$1,579				$403		
η_{jt}			$873				$386	
$\eta_{jt} > 0$				$689				$504
$\eta_{jt} < 0$				$1,495				$252
ϵ_{jt}			$336				$353	
$\epsilon_{jt} < 0$				$252				$319
$\epsilon_{jt} > 0$				$436				$386

Table V shows a set of OLS panel regressions controlling for firm and worker characteristics. All regressions include firm-level controls (which include, firm age, lagged firm TFP level, firm employment, and total firm ability), worker-level controls (which include, a polynomial in age, lagged worker experience, lagged log wage level, lagged tenure in the firm, gender, and lagged log ability), the inverse of Mills ratio to control for selection, and year fixed effects. $*p < 0.1, **p < 0.05, ***p < 0.01$. Robust standard errors are clustered at the firm-level.

Table VI – Passthrough from Firm and Industry TFP shocks to Wages

Dep. Variable	Change of Log Hourly Wages, $\Delta\hat{w}_{i,j,t}$				
	(1)	(2)	(3)	(4)	(5)
	Industry and Aggregate Shocks		Switchers	Expansions	Recessions
Specification:	All	Pos/Neg			
$\Delta\nu_{jt}$	.076***	.058***			
	(.004)	(.004)			
$\Delta\nu_{jt} \times \mathbb{I}_{\Delta\nu_{jt}<0}$		.060***			
		(.006)			
$\Delta\nu_t^k$	.024***	.00			
	(.006)	.015			
$\Delta\nu_t^k \times \mathbb{I}_{\Delta\nu_t^k<0}$		.046*			
		(.023)			
η_{jt}			.025***	.056***	.014
			(.007)	(.004)	(.032)
$\eta_{jt} \times \mathbb{I}_{\eta_{jt}<0}$			.002	.080***	.127***
			(.002)	(.007)	(.041)
ϵ_{jt}			.057***	.025***	.032***
			(.010)	(.006)	(.008)
$\epsilon_{jt} \times \mathbb{I}_{\epsilon_{jt}<0}$			$-$.018	.021**	$-$.007***
			(.018)	(.009)	(.018)
$Mills_{it}$	-.209***	-.275***	-.012***	-.230***	-.333***
	(.014)	(.016)	(.003)	(.020)	(.035)
R^2	.78	.78	.70	.81	.44
Obs. (M)	6.47	6.47	0.55	4.2	1.1
	Monetary Value of a Shock to Firm TFP (US$ 2010)				
$\Delta\nu_{jt}$	$1,041				
$\Delta\nu_{jt} > 0$		$789			
$\Delta\nu_{jt} < 0$		$1,595			
$\Delta\nu_t^k$	$67.2				
$\Delta\nu_t^k > 0$		$0.0			
$\Delta\nu_t^k < 0$		$117			
$\eta_{jt} > 0$			$2,099	$638	$167
$\eta_{jt} < 0$			$1,914	$1,528	$1,662
$\epsilon_{jt} < 0$			$554	$252	$336
$\epsilon_{jt} > 0$			$369	$453	$269

Table VI shows a set of OLS panel regressions controlling for firm and worker characteristics. All regressions include firm-level controls (which include, firm age, lagged firm TFP level, firm employment, and total firm ability), worker-level controls (which include, a polynomial in age, lagged worker experience, lagged log wage level, lagged tenure in the firm, gender, and lagged log ability), the inverse of Mills ratio to control for selection, and year fixed effects. In column (4), expansion years are all years in our sample with the exception of 2002-2003 (which experienced a mild recession) and 2008-2009. The results for 2008 and 2009 are displayed in column (5). $*p < 0.1, **p < 0.05, ***p < 0.01$. Robust standard errors are clustered at the firm-level.

Table VII – Comparing Passthrough Under Different Assumptions

	(1)	(2)	(3)	(4)	(5)	(6)
	Δw	Δw	Δw_h	Δw_h	Δw_h	Δw_h
β	.079***	.063***	.035***	.032***	.042***	.046
	(.002)	(.002)	(.001)	(.001)	(.002)	(.003)
Firm shock	VA	VAres	VAres	VAres_{akm}	VAres_{akm}	$\Delta\nu_{jt}$
Individual Ability	N	N	N	N	Y	Y
R^2	.49	.49	.17	.18	.79	.78
Pct Effect	3.4%	2.6%	1.5%	1.6%	2.1%	1.2%
Avg Effect	$1,911	$1,492	$873	$955	$1,243	$705
Correction	None	Residual	Hours	Quality	Quality	TFP

Table VII shows a set of OLS panel regressions controlling for firm and worker characteristics. w and w_h are annual income and hourly wages. Firm shocks are changes in logs of: value added (VA), residualized value added from an OLS regression of value added on firm inputs (VAres), residualized value added using the AKM-adjusted measure of labor (VAres_{akm}) and AKM-adjusted total TFP (ν_{jt}). All regressions include firm-level controls (which include, firm age, lagged firm shocks, and firm employment), worker-level controls (which include, a polynomial in age, lagged worker experience, lagged log wage level, lagged tenure in the firm, and gender), and year fixed effects. These results are not selection corrected. $*p < 0.1, **p < 0.05, ***p < 0.01$. Robust standard errors are clustered at the firm-level.

Figure 1 – Passthrough from Firms' Growth to Workers' Wages

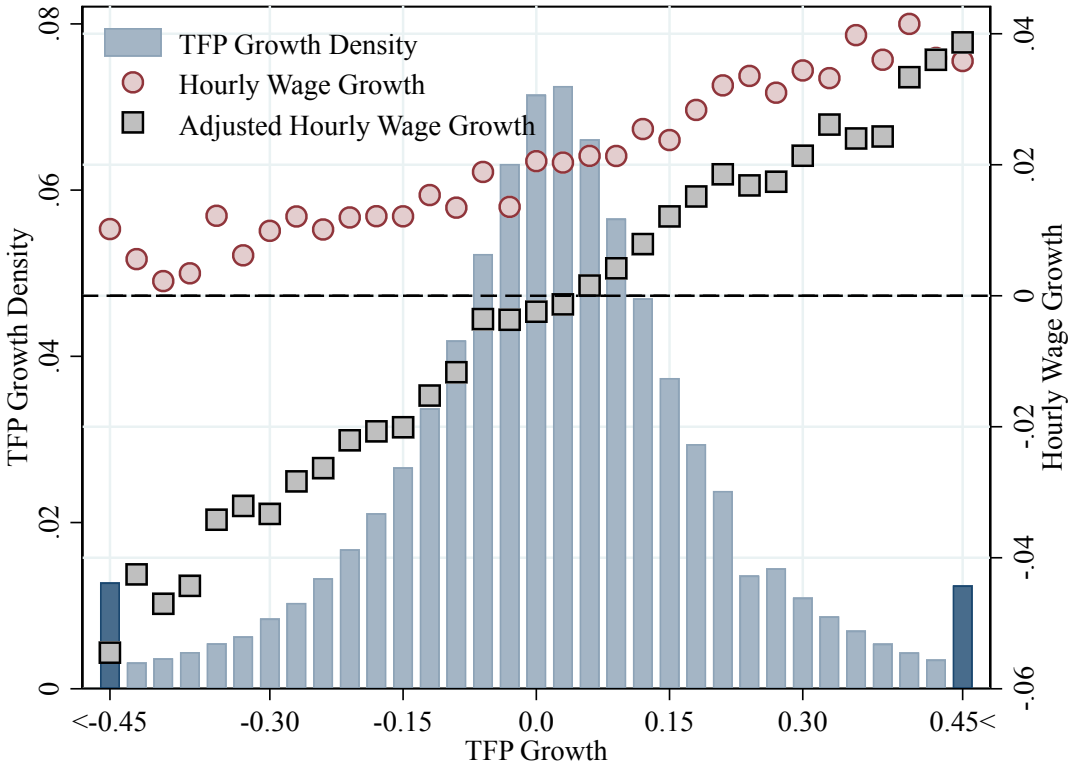


Figure 1 is based on a pooled sample of firms and workers between years 1992 to 2010. The blue bars show the share of firms within different bins of the TFP growth distribution (left y-axis). To construct the bins we separate in 41 bins between -.45 and 45. The left and right-most bins, marked in darker blue, encompass the remaining left and right tails of the distribution, and thus are not the same size as the other bins. The red dots show the average hourly wage growth for all workers employed by firms within a bin (right y-axis). The black squares show the average hourly wage growth after controlling for worker characteristics, firms characteristics, and endogenous selection. To avoid the disclosure of any sensitive information, we report the mean of the observations within a percentile-band rather than the individual observation at the percentile cutoff.

Figure 2 – Connected Sets using Multiple Jobs

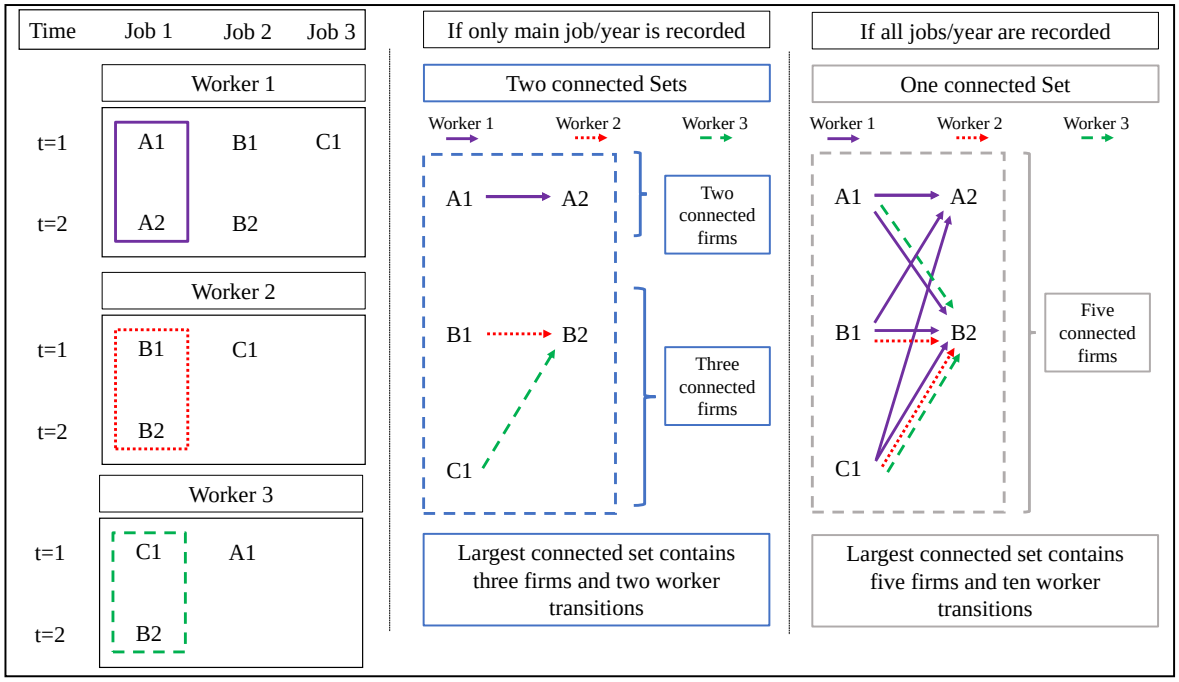
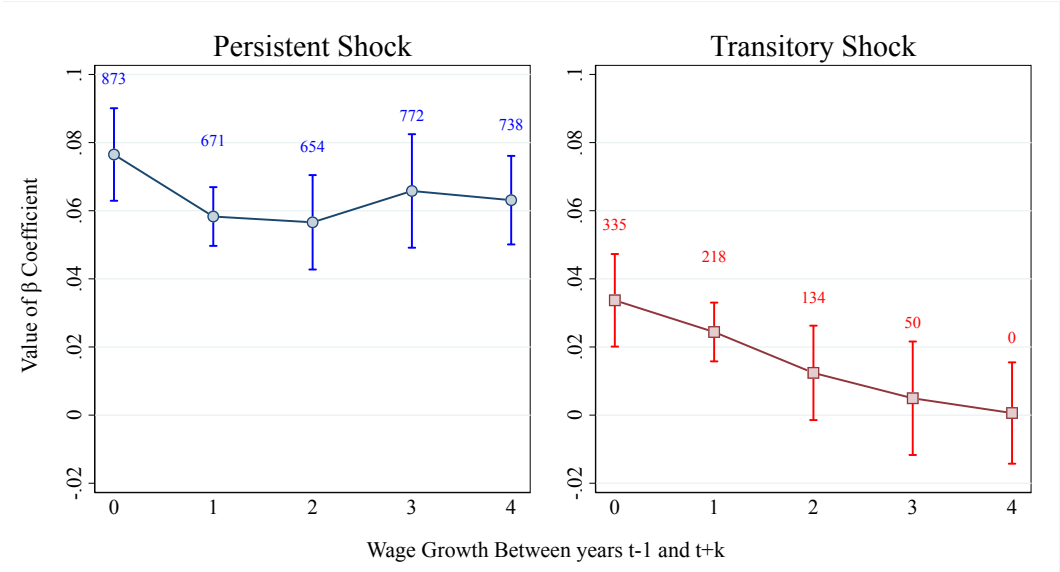


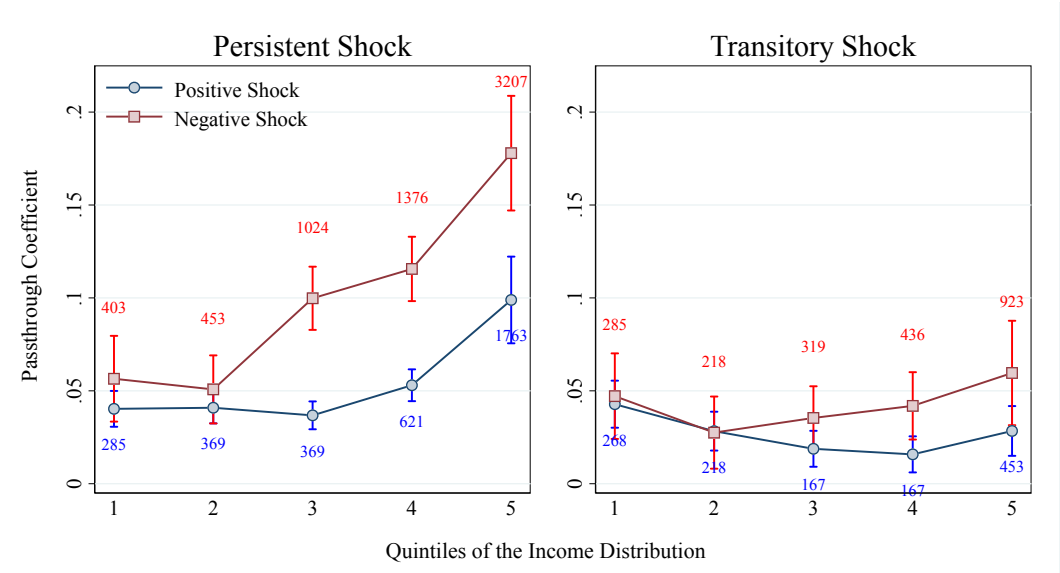
Figure 2 shows how we achieve identification in an AKM-style two-way fixed effect setting with firm-year fixed effects and multiple jobs per worker-year. The left panel shows a theoretical set of jobs across two years for three different workers (represented by solid purple, dotted red and dashed green lines). In this example, worker 1 has three jobs in period 1, working at firms A, B, and C. In period 2, worker 1 has two jobs – working at firm A and B. Because we estimate firm effects separately for each year, we treat each firm-year observation as a separate firm. Thus A1 and A2 refers to firm A in two different periods. The middle panel shows the network graph of all 5 firm-year nodes if we were to only consider each worker's first or primary job. For example, worker 1 moves from A1 in period 1 to A2 in period 2, while worker 3 moves from C1 to B2. The result is two (disjoint) connected sets, the first with firms A1 and A2, and the second (largest connect set) with firms B1, B2 and C1. Each firm is connected to the rest of their set with just a single worker transition. The right-most panel shows the network graph when we consider all of the available worker job information. In this setting, each first-period job worked by an individual is connected to every second-period job worked by that same individual, leading to a connected set including all 5 firms. Moreover, each firm in this larger connected set is connected by at least 3 worker transitions to the rest of the set, strengthening identification of the firm and worker fixed effects.

Figure 3 – Shocks to Firms Have a Long-Lasting Impact on Workers' Wages



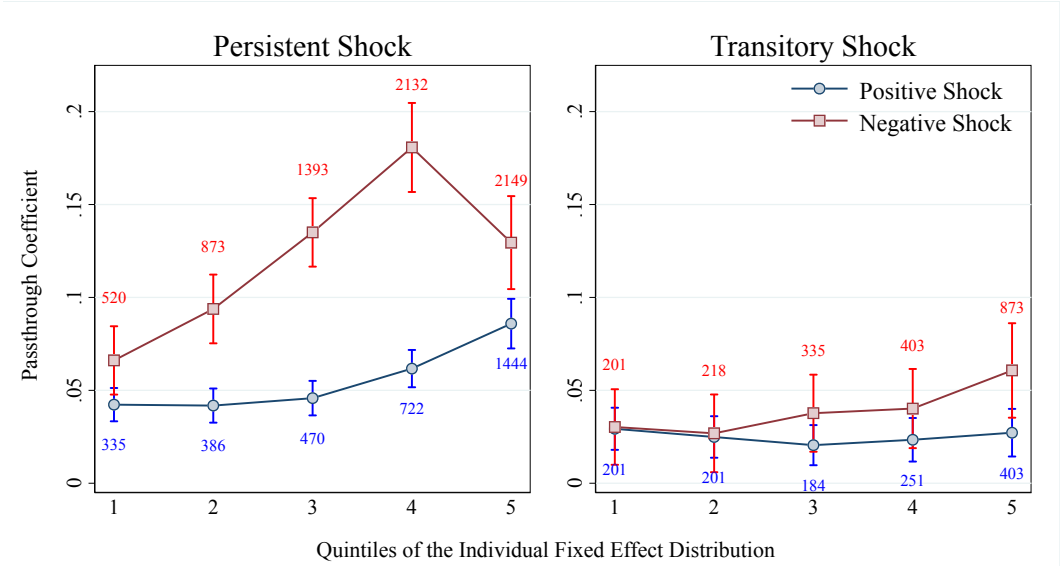
Note: Figure 3 shows the elasticity of hourly wages to a persistent (transitory) shock to firms productivity. In each plot the vertical lines show 95% confidence intervals.

Figure 4 – Passthrough by Wage Quintiles



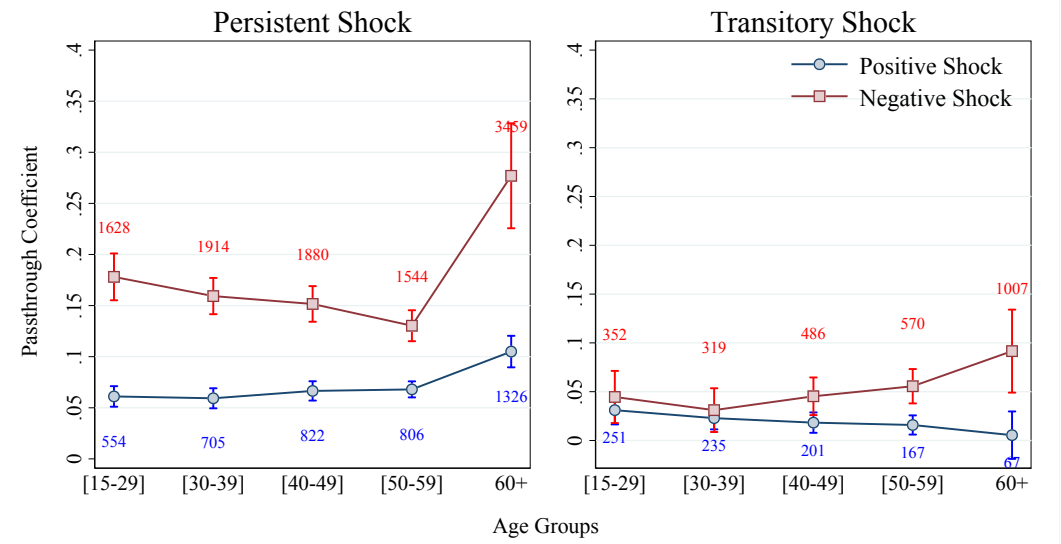
Note: Figure 4 shows the elasticity of hourly wages to a persistent (transitory) shock to firms productivity. In each plot the vertical lines show 95% confidence intervals. In each plot, the number above the lines represent the monetary value of a shock of one standard deviation. All monetary values are calculated relative to the average annual labor earnings within the corresponding group.

Figure 5 – Passthrough by Ability Groups



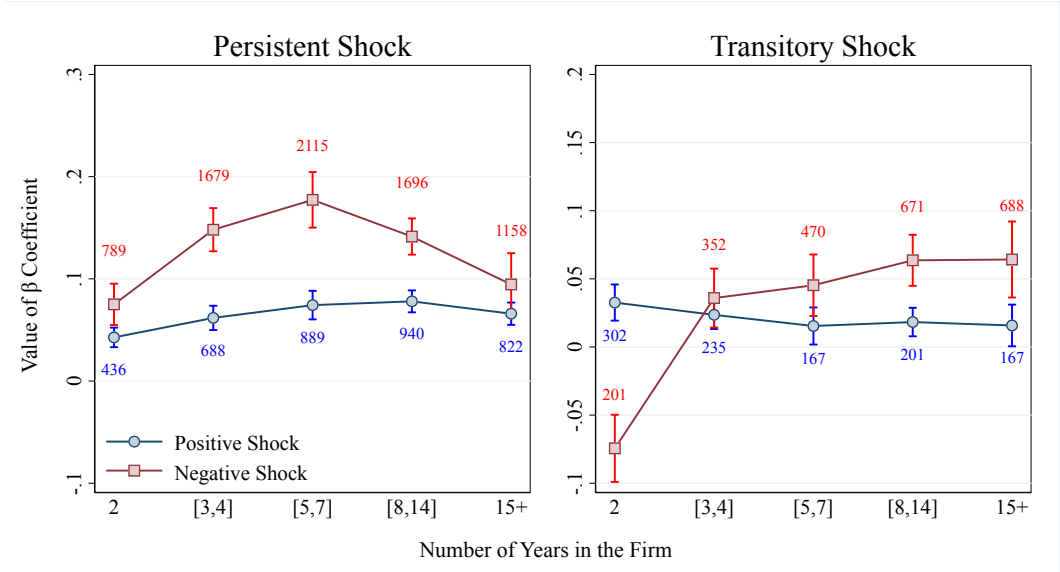
Note: Figure 5 shows the elasticity of hourly wages to a persistent (left panel) and transitory (right panel) productivity shock within quintiles of the workers' ability distribution measured by the value of $\exp(\hat{\alpha}_i + \hat{\Gamma} X_{it})$ derived from our AKM estimates.In each plot the vertical lines show 95% confidence intervals. The number above the lines represent the monetary value of a shock of one standard deviation. All monetary values are calculated relative to the average annual labor earnings within the corresponding group.

Figure 6 – Passthrough by Age Groups



Note: Figure 6 shows the elasticity of hourly wages to a persistent (left panel) and transitory (right panel) productivity shock. In each plot the vertical lines show 95% confidence intervals. The number above the lines represent the monetary value of a shock of one standard deviation. All monetary values are calculated relative to the average annual labor earnings within the corresponding group.

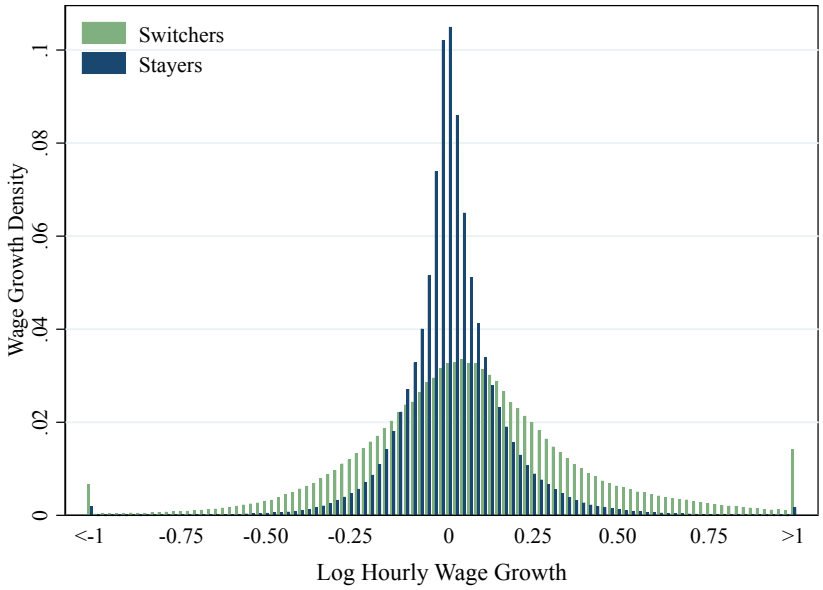
Figure 7 – Passthrough by Tenure Groups



Note: Figure 7 shows the elasticity of hourly wages to a persistent (left panel) and transitory (right panel) productivity shock. In each plot the vertical lines show 95% confidence intervals. The number above the lines represent the monetary value of a shock of one standard deviation. All monetary values are calculated relative to the average annual labor earnings within the corresponding group.

Figure 8 – Log Hourly Wage Growth and Firm Productivity

(a) Log Wage Growth Density for Stayers and Switchers



(b) Switchers: Log Hourly Wage Growth and log Firm TFP

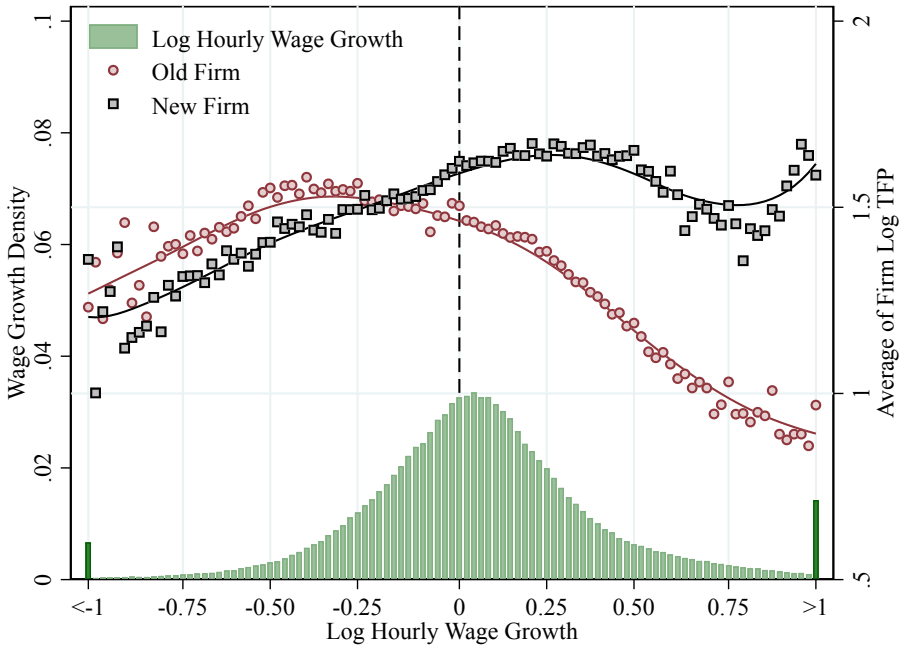
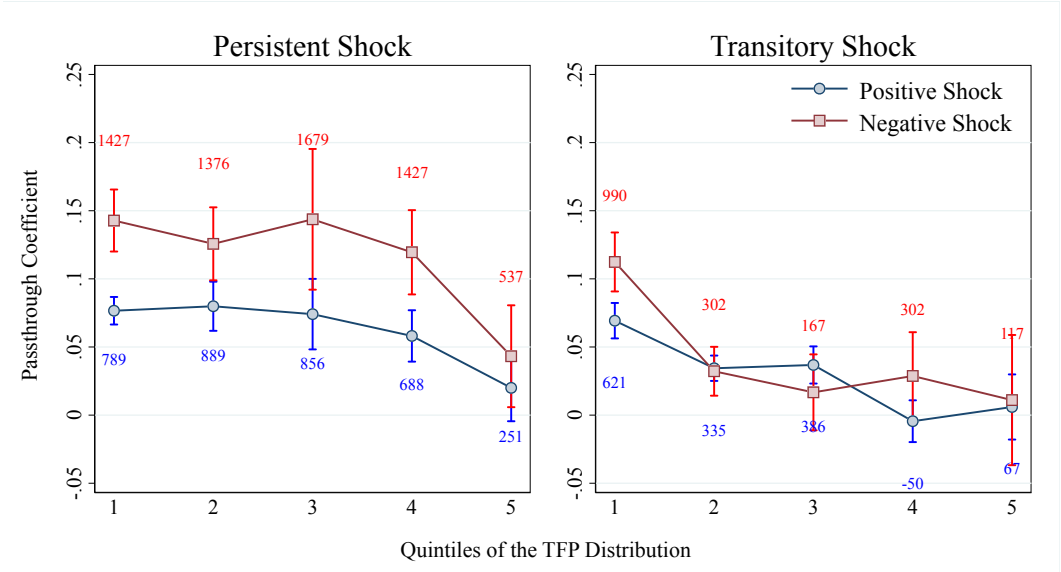


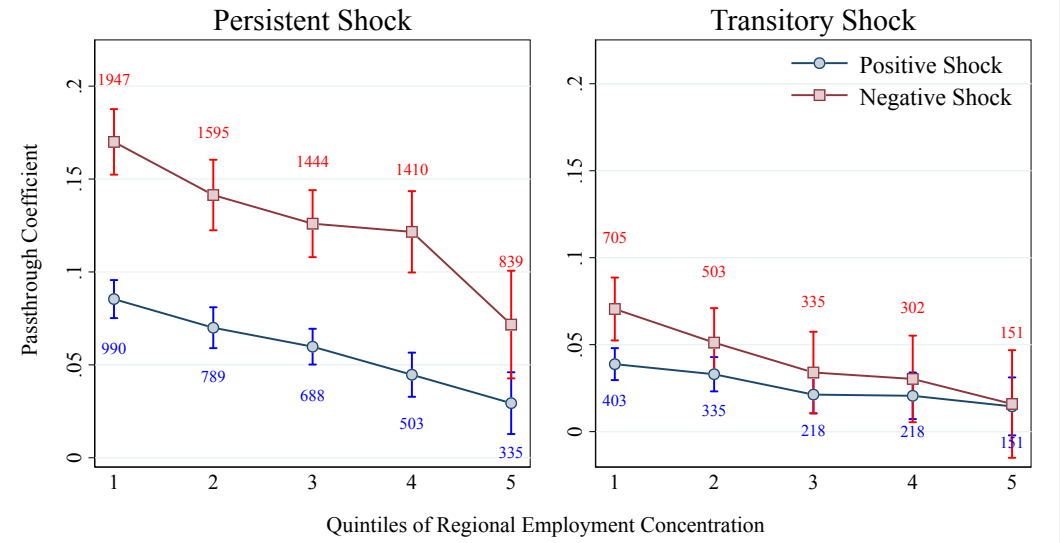
Figure 8 is based on a pooled sample of stayers and switchers(workers that move across firms between firms $t-1$ and t) and their corresponding firms. In the top panel, the green bars (navy bars) show the share of switchers (stayers) within different bins of the hourly wage growth distribution (left y-axis). To construct the graph we partition the wage growth distribution into 101 separate bins between -1 and 1. The left and right-most bins, marked in darker green, encompass the remaining left and right tails of the distribution, and thus are not the same size as the other bins. The bottom panel shows the density for switchers only. The red dots show the average log TFP for the firms that employed the workers in period $t-1$; The black squares show the average TFP for the firms that employed the workers in each bin in period t. The lines are lowess smoothing estimates.

Figure 9 – Passthrough by Firm Productivity Groups



Note: Figure 9 shows the elasticity of hourly wages to a persistent (left panel) and transitory (right panel) productivity shock. In each plot the vertical lines show 95% confidence intervals. The number above the lines represent the monetary value of a shock of one standard deviation. All monetary values are calculated relative to the average annual labor earnings within the corresponding group.

Figure 10 – Passthrough by Employment Share Groups

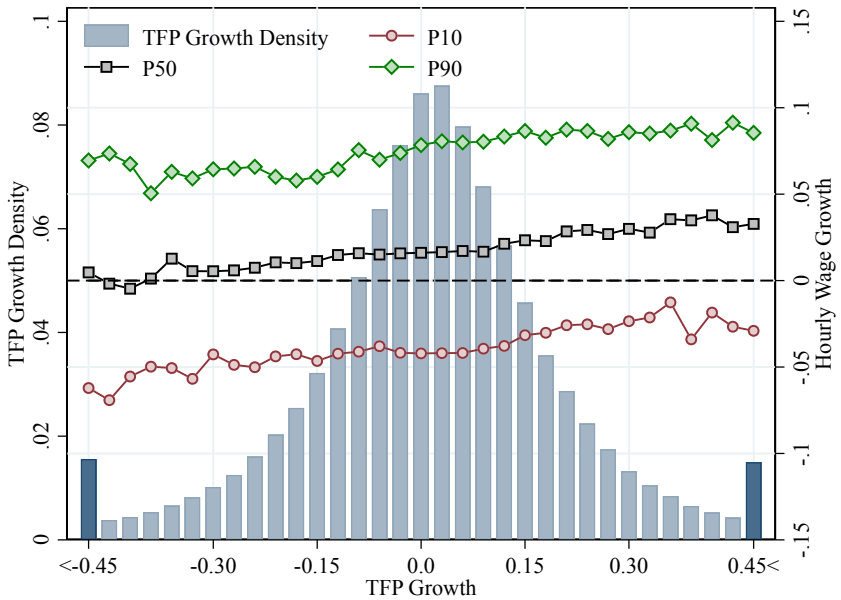


Note: Figure 10 shows the elasticity of hourly wages to a persistent (left panel) and transitory (right panel) productivity shock. In each plot the vertical lines show 95% confidence intervals. The number above the lines represent the monetary value of a shock of one standard deviation. All monetary values are calculated relative to the average annual labor earnings within the corresponding group.

A Appendix

Figure A.1 – Firms' Growth to Percentiles of Workers' Wages

(a) Hourly Wages



(b) Adjusted Hourly Wages

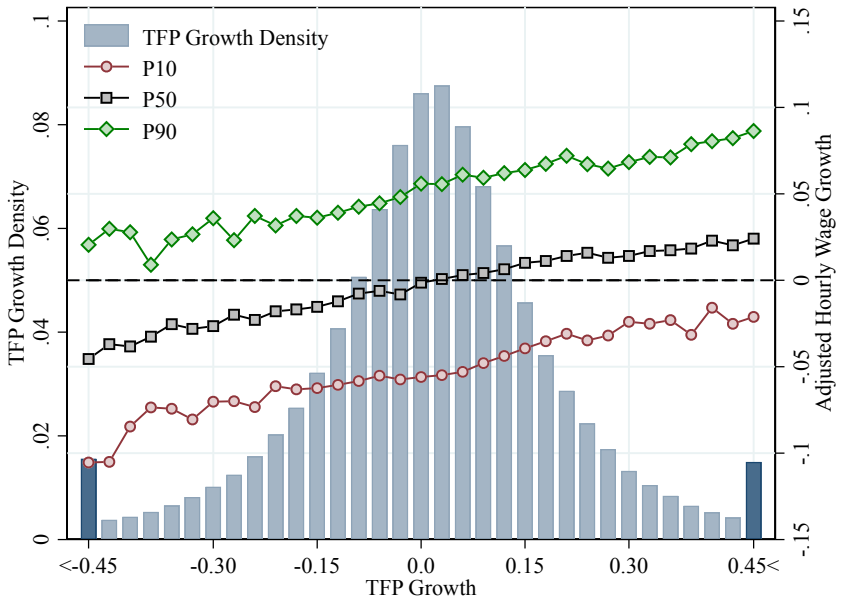
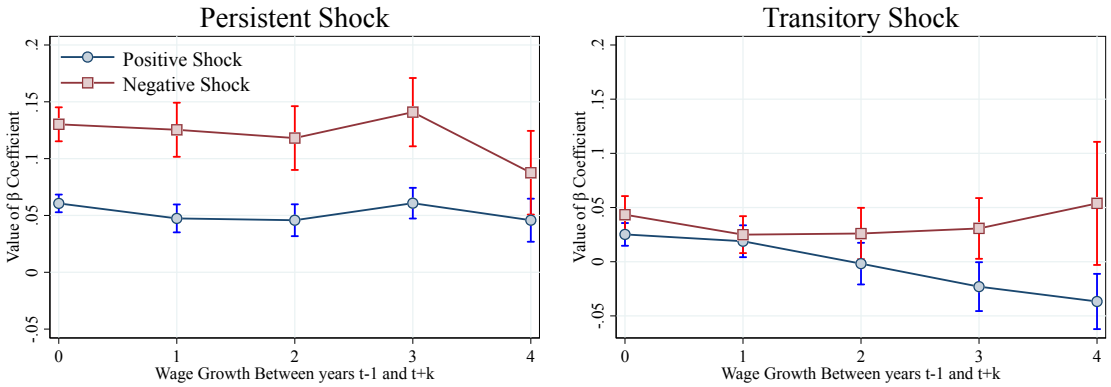


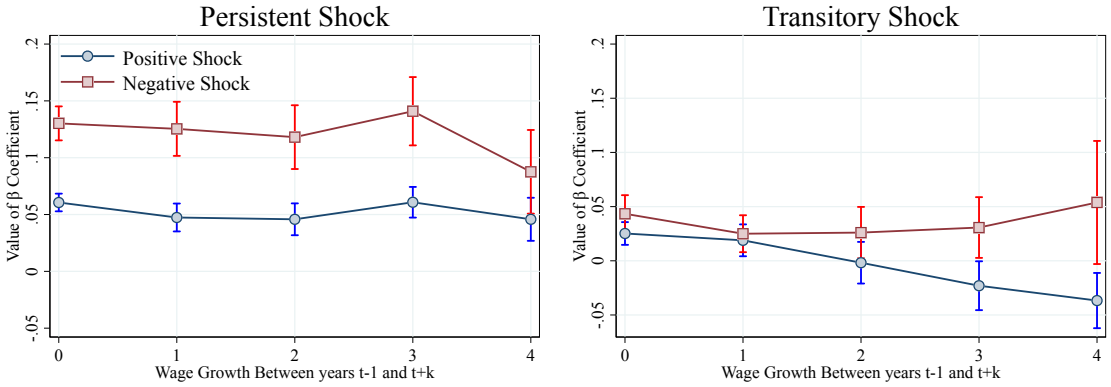
Figure A.1 is based on a pooled sample of firms and workers between years 1992 to 2010. The blue bars show the share of firms within different bins of the TFP growth distribution (left y-axis). To construct the graph we separate firms into 41 equally-sized bins between -.45 and 45 based on their level of TFP growth. The left and right-most bins, marked in darker blue, encompass the remaining left and right tails of the distribution. The right axis of each panel shows the within-percentile means of the hourly wage growth (top panel) and adjusted hourly wage growth distributions (bottom panel). To avoid the disclosure of any sensitive information, we report the mean of the observations *within* a percentile-band rather than the individual observation at the percentile cutoff.

Figure A.2 – Positive and Negative Shocks Have Long-Lived Impact on Wages



Note: Figure A.2 shows the elasticity of hourly wages to firm productivity. In each plot, hourly wage growth is measured as the change between year t and $t+k$ where k is plotted in the x-axis. Firms' productivity shocks are measured by η_{jt} (left panel) and ϵ_{jt} (right panel). In each plot the vertical lines show 95% confidence intervals.

Figure A.3 – Positive and Negative Shocks Have Long-Lived Impact on Wages: Balanced Panel



Note: Figure A.3 shows the elasticity of hourly wages to firm productivity. In each plot, hourly wage growth is measured as the change between year t and $t+k$ where k is plotted in the x-axis. Firms' productivity shocks are measured by η_{jt} (left panel) and ϵ_{jt} (right panel). In each plot the vertical lines show 95% confidence intervals.

Figure A.4 – Hourly Wage Growth for Switchers and Firm Productivity

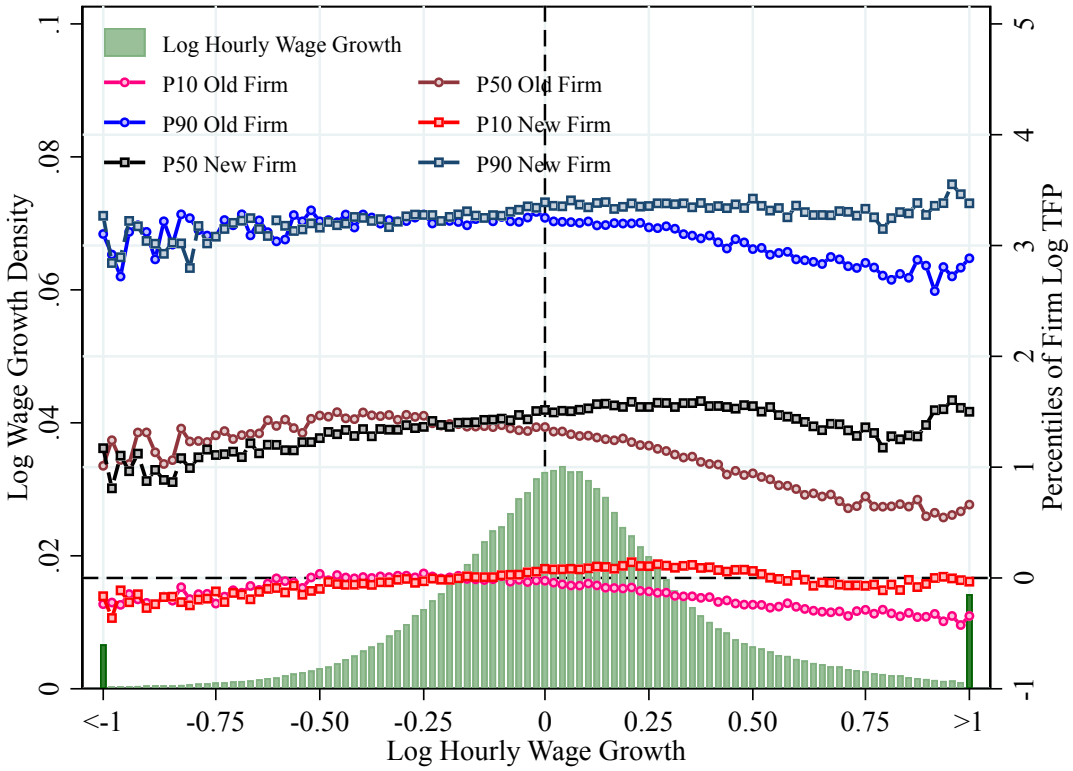
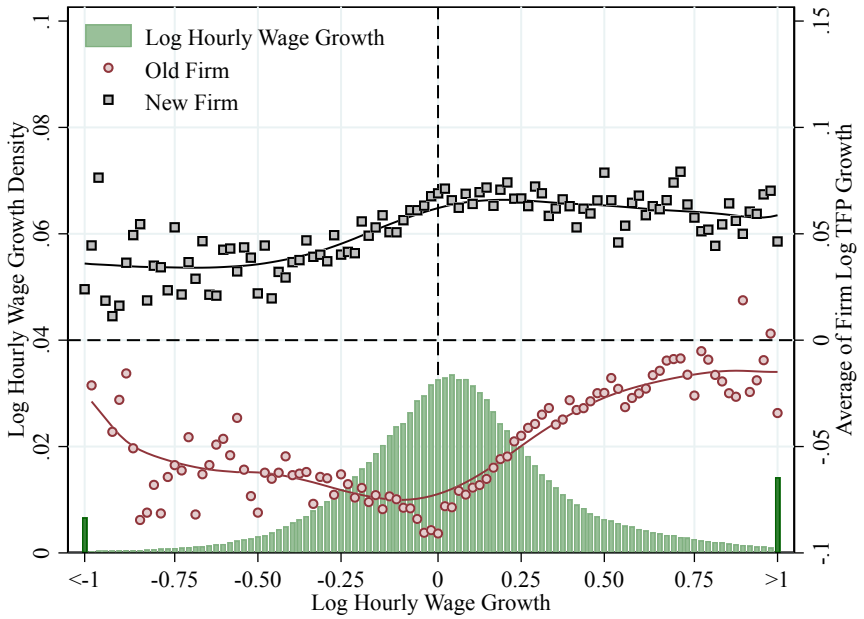


Figure A.4 is based on a pooled sample of switchers (workers that move across firms between firms $t-1$ and t) and their corresponding firms. The green bars show the share of workers within different bins of the hourly wage growth distribution (left y-axis). To construct the bins we separate in 101 bins between -1 and 1. To construct the graph we partition the wage growth distribution into 101 separate bins between -1 and 1. The left and right-most bins, marked in darker green, encompass the remaining left and right tails of the distribution, and thus are not the same size as the other bins. The circles show percentiles of the log TFP distribution for the firms that employed the workers in period $t-1$; The squares show percentiles of the log TFP distribution for the firms that employed the workers in period t. To avoid the disclosure of any sensitive information, we report the mean of the observations *within* a percentile-band rather than the individual observation at the percentile cutoff.

Figure A.5 – Hourly Wage Growth for Switchers and Productivity Growth

(a) Average TFP Growth



(b) Percentiles of TFP Growth

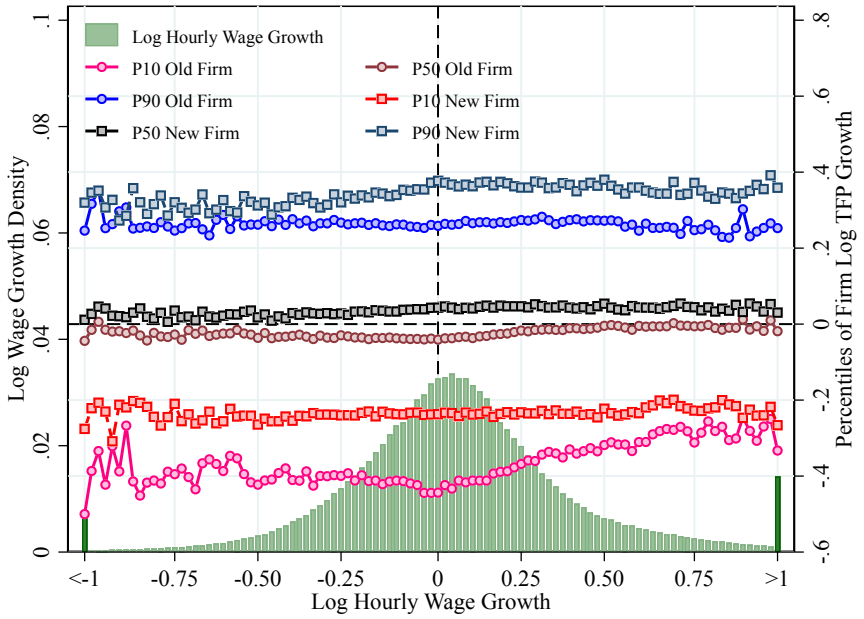


Figure A.5 is based on a pooled sample of switchers (workers that move across firms between firms $t-1$ and t) and their corresponding firms. The green bars show the share of workers within different bins of the hourly wage growth distribution (left y-axis). To construct the graph we partition the wage growth distribution into 101 separate bins between -1 and 1. The left and right-most bins, marked in darker green, encompass the remaining left and right tails of the distribution, and thus are not the same size as the other bins. The top panel shows average log-TFP growth for both source and destination firms for switchers. The bottom panel shows percentiles of the TFP growth distribution for each wage growth bin. To avoid the disclosure of any sensitive information, we report the mean of the observations *within* a percentile-band rather than the individual observation at the percentile cutoff.